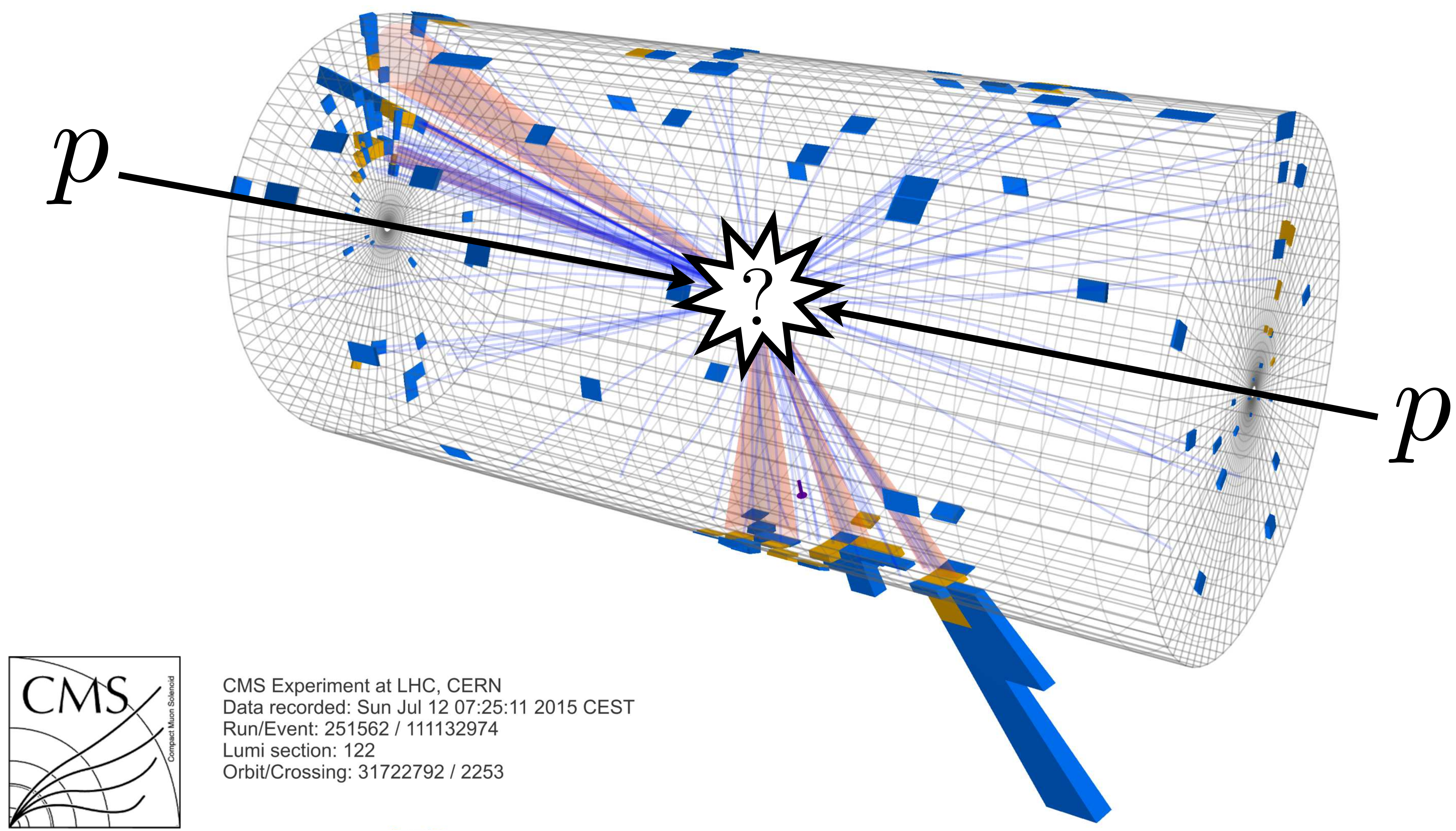
Collision Course

Particle Physics meets Machine Learning

Jesse Thaler

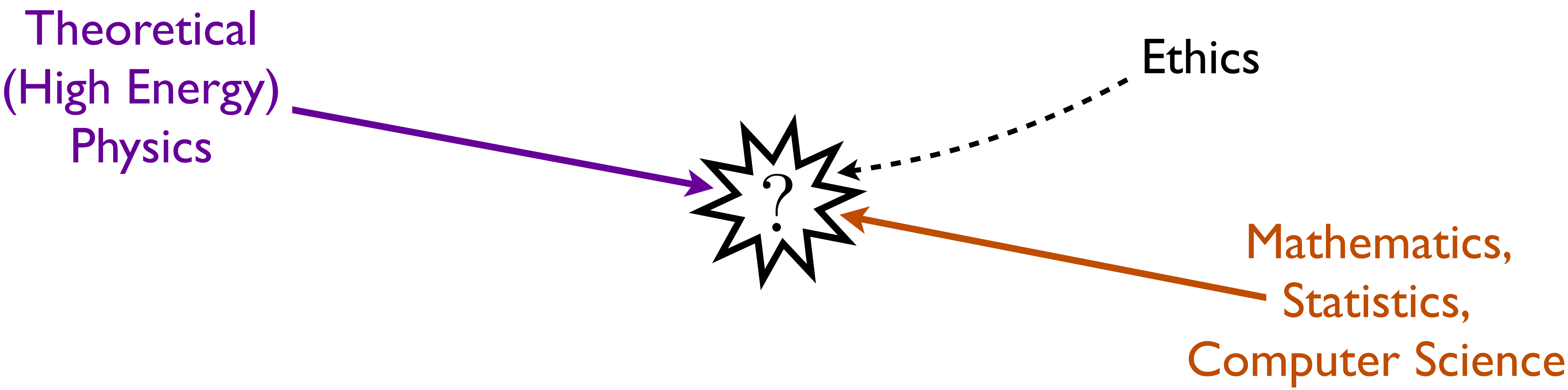
Physics Faculty Lunch Talk, MIT — September 19, 2019

"Collision Course"



"Collision Course"

"Theoretical Physics for Machine Learning"
Aspen Center for Physics, January 2019

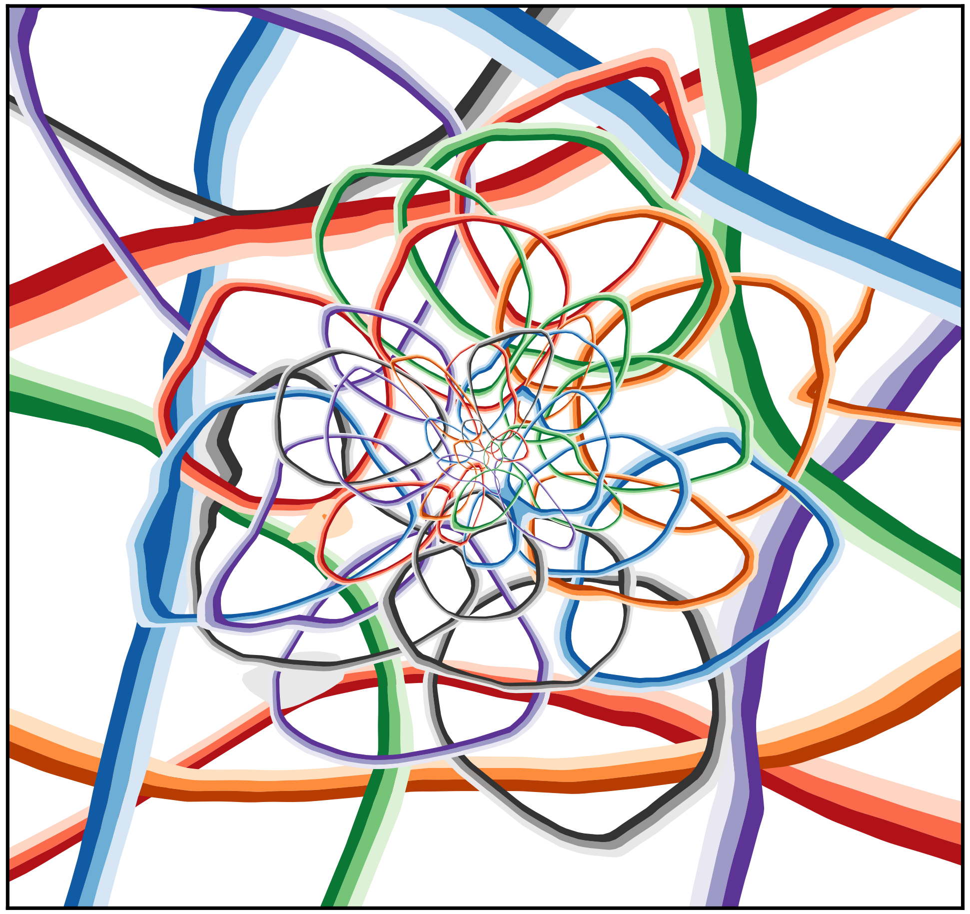


*New insights into particle physics**
*facilitated by advances in machine learning**

(and vice versa?)

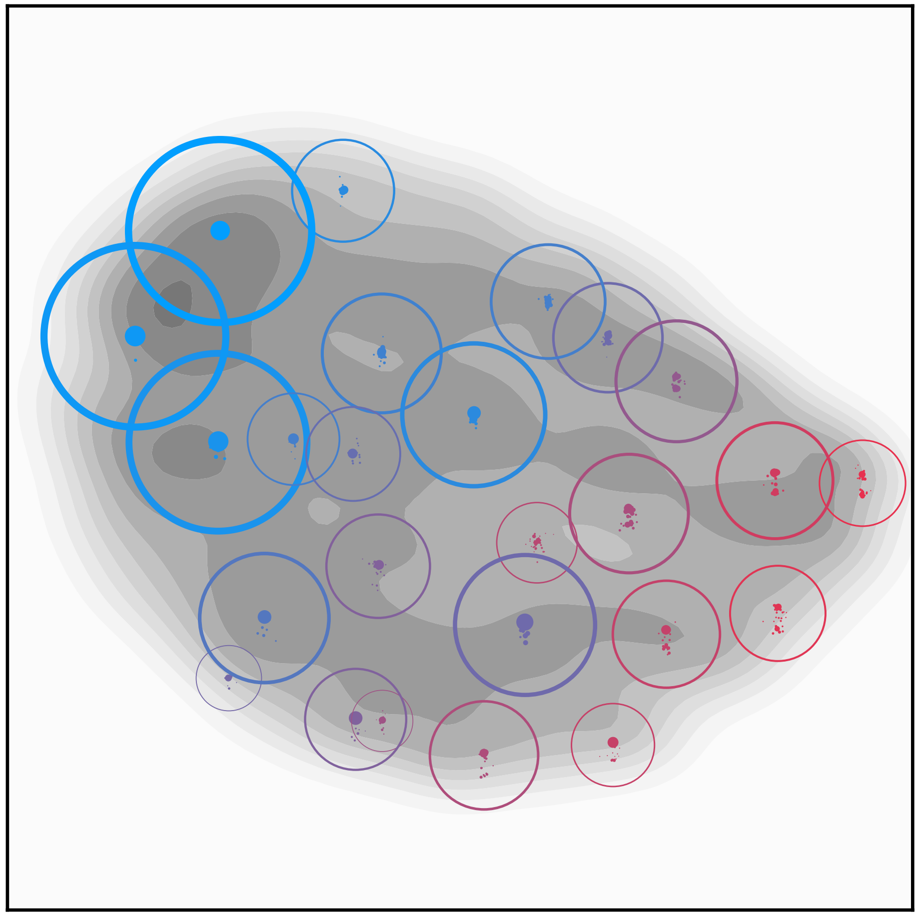
Today's Talk: Two Anecdotes

Teaching a Machine to "Think Like a Physicist"



[Komiske, Metodiev, JDT, JHEP 2019]

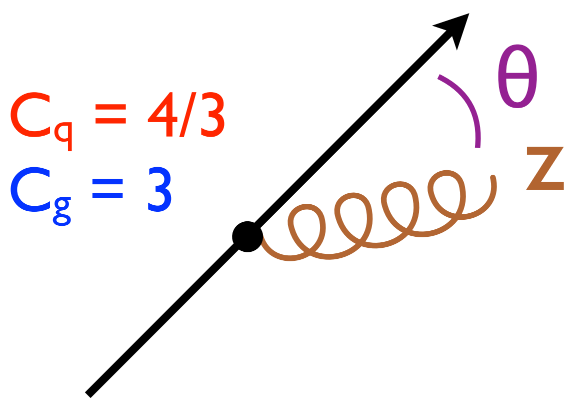
Letting Collider Data Speak for Itself



[Komiske, Mastandrea, Metodiev, Naik, JDT, submitted to PRD; based on Komiske, Metodiev, JDT, PRL 2019]

Data analysis strategies motivated by the symmetries and structures of particle physics

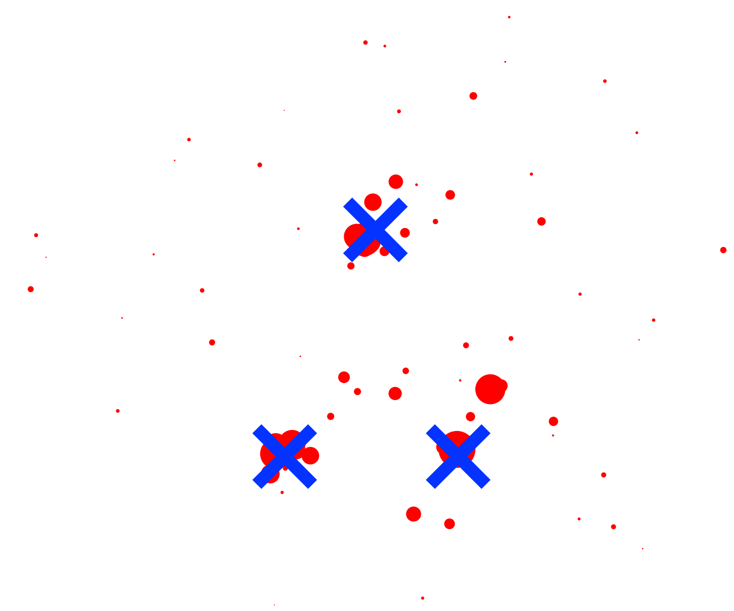
Exploiting a Core Prediction of QCD



$$\mathrm{d}P_{i\to ig} \simeq \frac{2\alpha_s}{\pi} C_i \frac{\mathrm{d}\theta}{\theta} \frac{\mathrm{d}z}{z}$$

[Altarelli, Parisi, NPB 1977]

N-prong Singularities of Gauge Theories



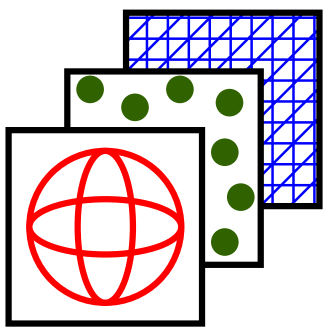
$$\tau_N(\mathcal{E}) = \min_{\text{axes}} \sum_i E_i \min_{a\in[1..N]} \{\theta_{a,i}\}$$

[Stewart, Tackmann, Waalewijn, PRL 2010;
JDT, Van Tilburg, JHEP 2011, JHEP 2012]

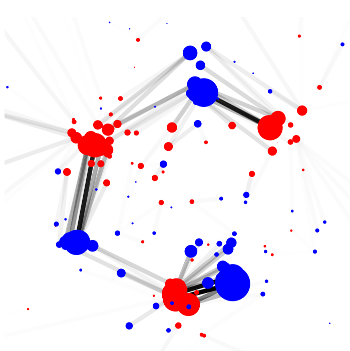
New perspectives on *key theoretical concepts*

Outline

Scenes from My Sabbatical



What is a Collider Event?



When are Collider Events Similar?

Scenes from My Sabbatical

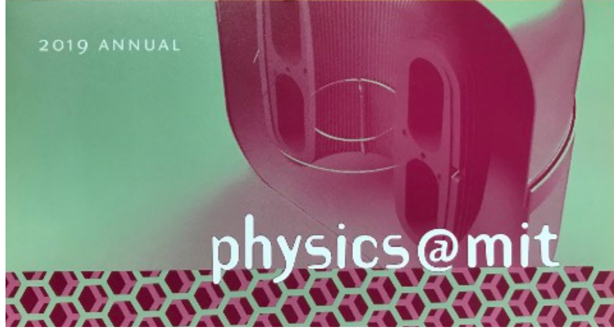
What is a Collider Event?

When are Collider Events Similar?

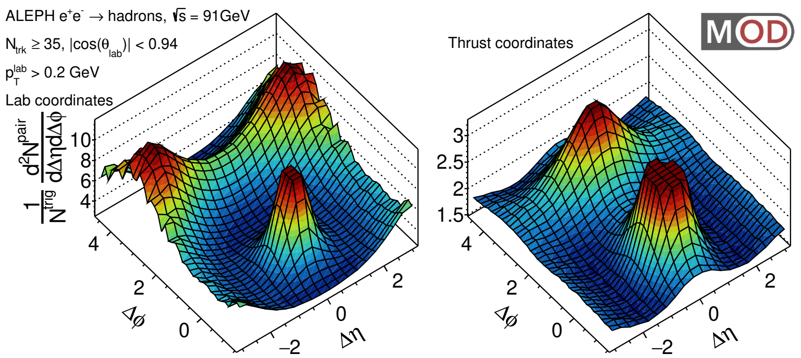
"Subway Sabbatical"

Thanks, VE RI TAS SF *!*

Can't get away from MIT…

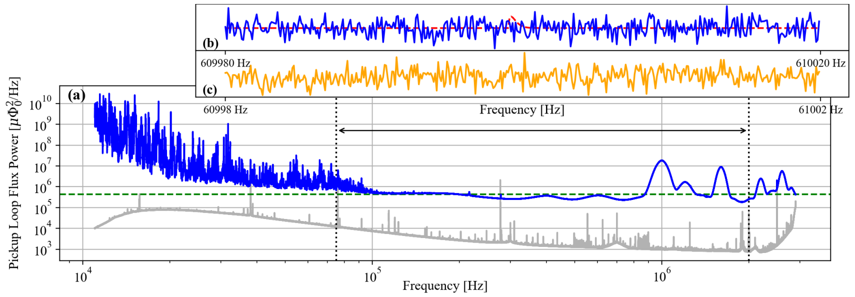


Back (to Back) to the Future



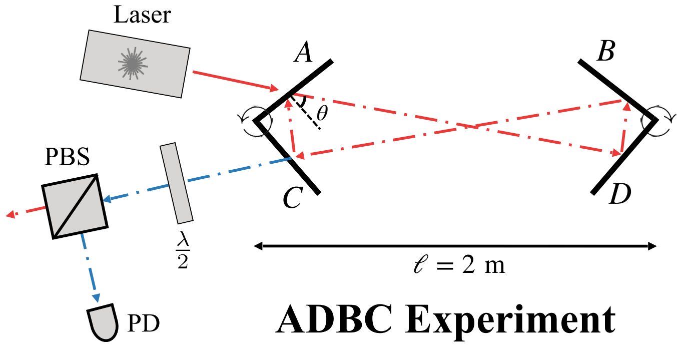
[Badea, Baty, Chang, Innocenti, Maggi, McGinn, Peters, Sheng, JDT, Lee, submitted to PRL]

ABRACADABRA



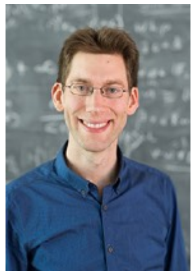
[Ouellet, Salemi, Foster, Henning, Bogorad, Conrad, Formaggio, Kahn, Minervini, Radovinsky, Rodd, Safdi, JDT, Winklehner, Winslow, PRL 2019]

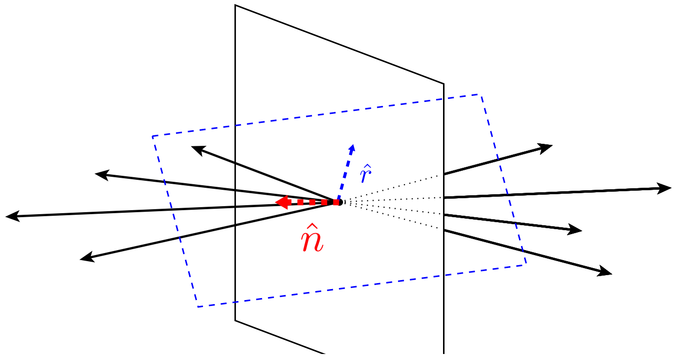
Shining Light on Dark Matter



[Liu, Elwood, Evans, JDT, PRD 2019]

Quantum Collider Physics



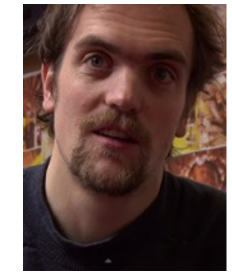


$$|i\rangle\ |j\rangle\ |\vec{p}_i\rangle\ |\vec{p}_j\rangle\ |\hat{r}_{ij}\rangle\ |\vec{P}_{ij}\rangle\ |T_{ij}\rangle$$

[Wei, Naik, Harrow, JDT, submitted to PRD; inspired by Farhi, PRL 1977]

Bringing people to MIT…

PHYSICS COMMUNITY VALUES



Our values

Well-being
We support each other at all times and remember that we are not alone.

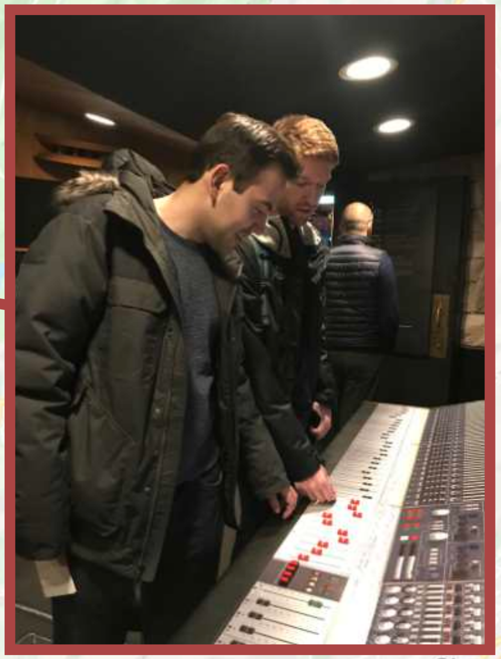
Respect
We value the multitude of ways to be a physicist and the many paths through our field and Department.

Inclusion
We strive to speak and act in ways that support and include all members of our community.

Collaboration
Physics is a social endeavor and we proudly collaborate with others to advance the field.

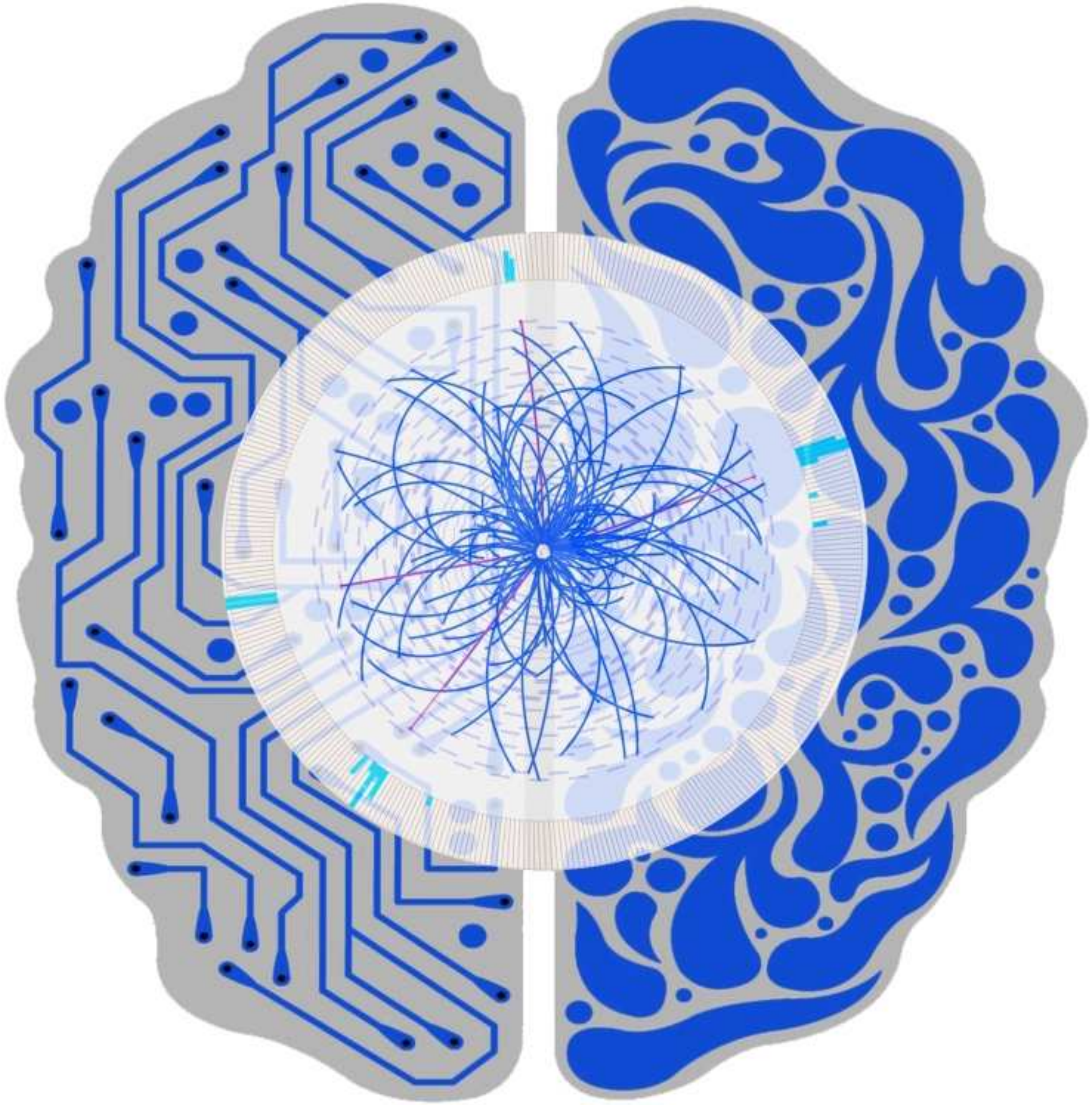
Mentorship
All physicists are here because of the mentorship we have received and continue to receive, and the mentorship we offer to others.

Taking MIT with me…



Eric Metodiev

Patrick Komiske

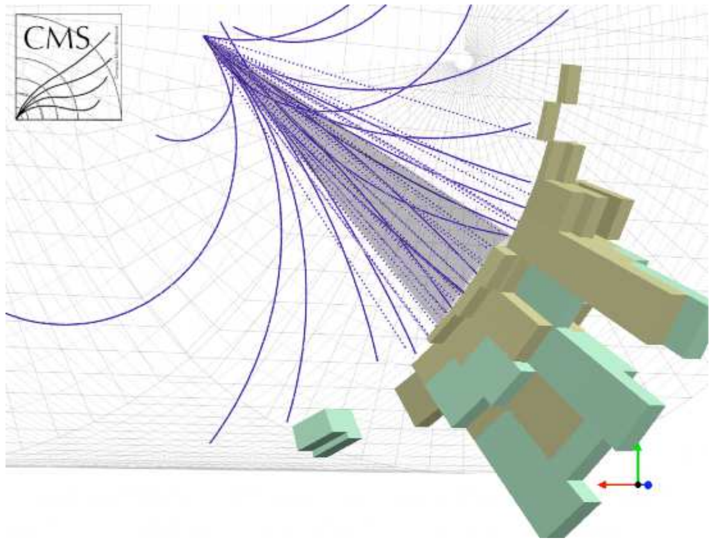


The Rise of Machine Learning

Cartoon of Machine Learning

"ML4Jets"
NYU, January 2020

For this talk: $\mathcal{J}$ = jet



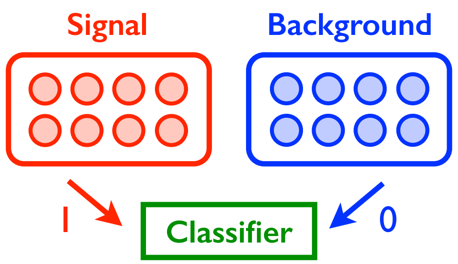
Properly specified problem

Many (labeled) examples $\{\mathcal{J}\}$

The Machine

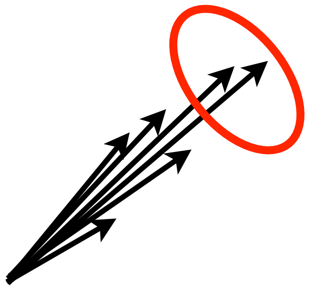
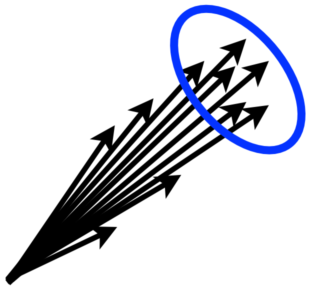
Solution $S(\mathcal{J})$

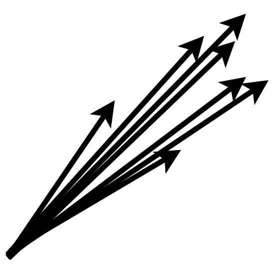
E.g.: Problem = Minimize loss function
Solution = Multi-layer neural network
Strategy = Stochastic gradient descent



E.g. Jet Classification

Key supervised learning task at LHC

e.g.  **Quark** $C_q = 4/3$ vs.  **Gluon** $C_g = 3 = 9/3$

Find $h\Big($  $\Big)$ such that

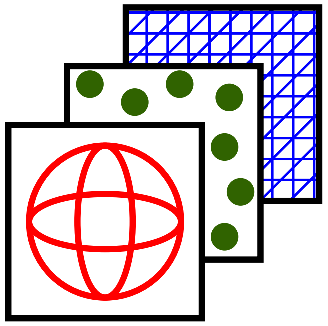
$$h(\text{Quark}) = 1$$

$$h(\text{Gluon}) = 0$$

Best you can do: $$h(\mathcal{J}) = \frac{p(\mathcal{J}|\mathrm{Q})}{p(\mathcal{J}|\mathrm{Q}) + p(\mathcal{J}|\mathrm{G})}$$

(Neyman-Pearson lemma)

Scenes from My Sabbatical

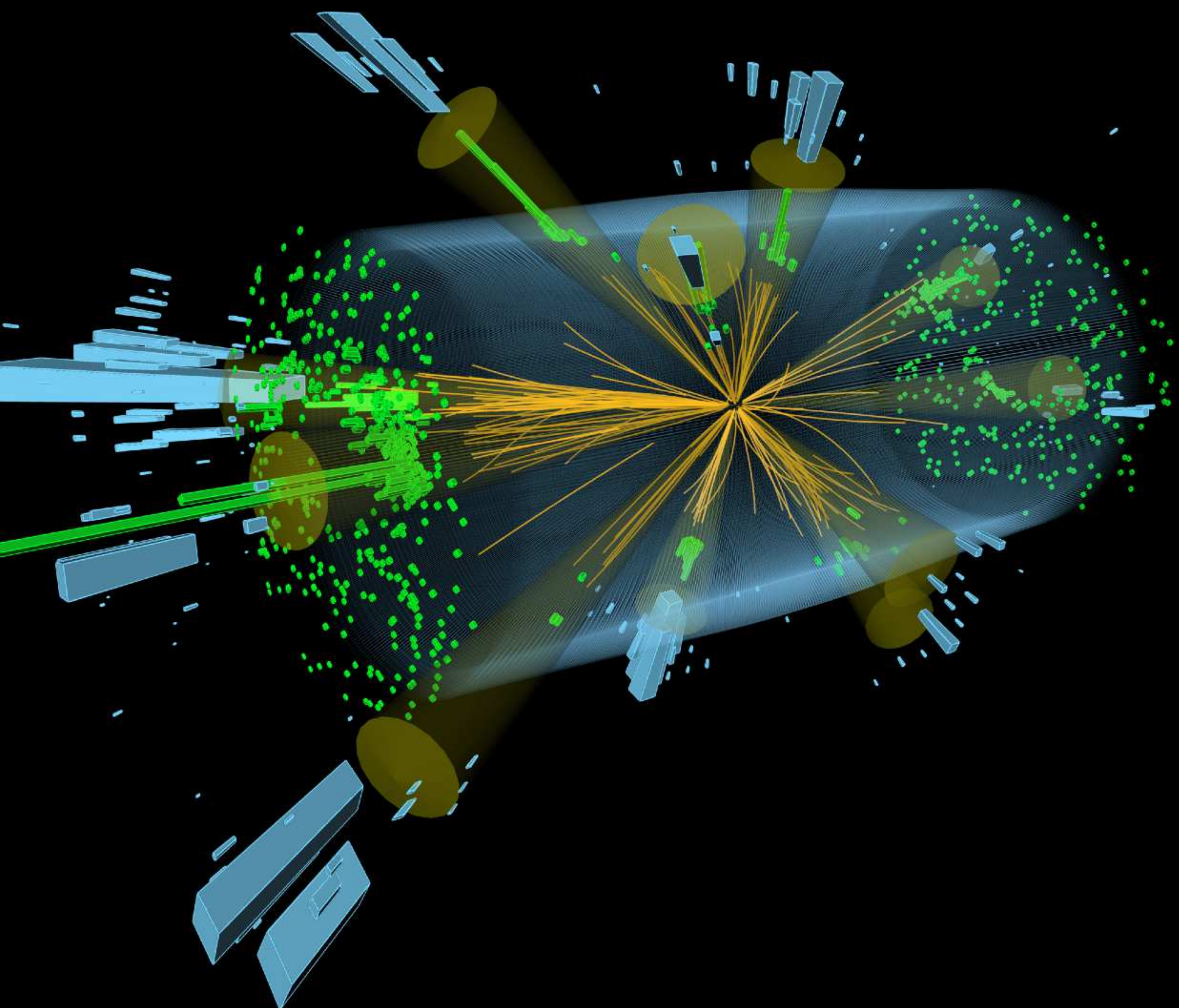


What is a Collider Event?

When are Collider Events Similar?

Collider Event

Collection of points in (momentum) space



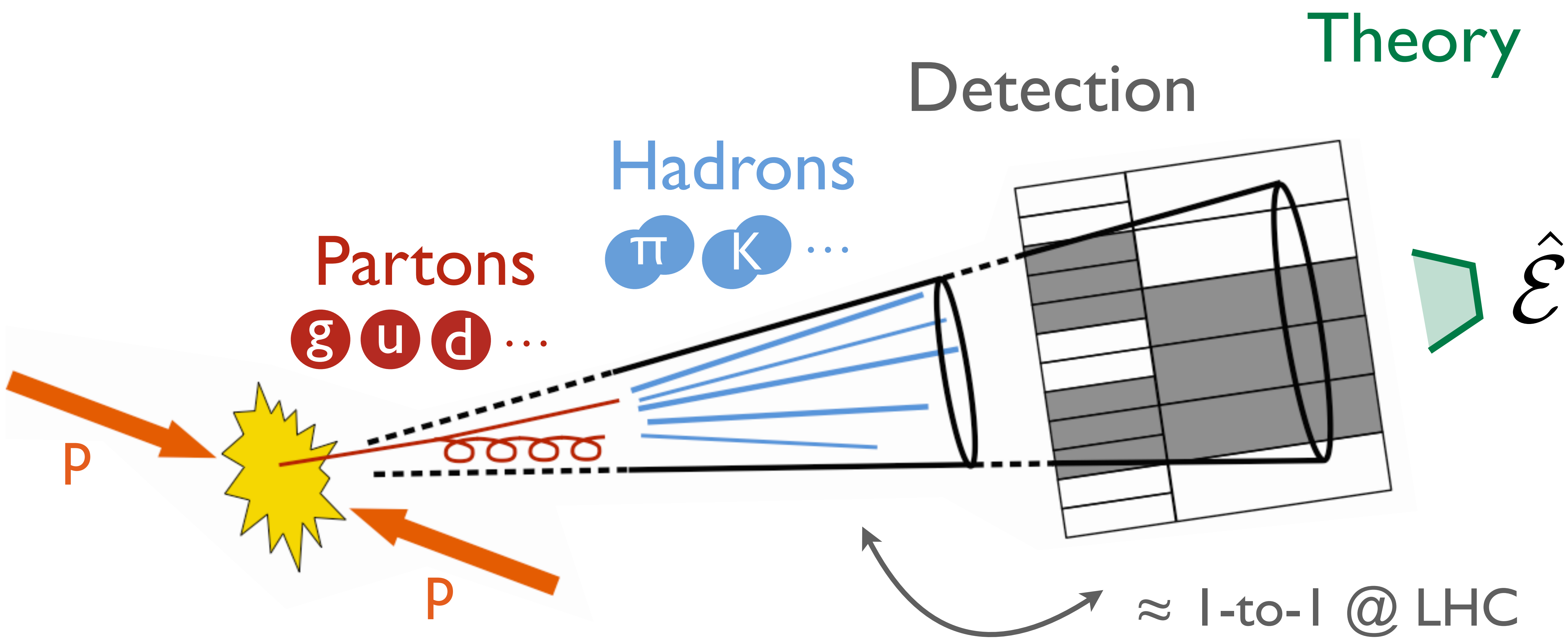
	T	E	H	M		
elementary		●			γ	photon
elementary	●	●			$e^{\pm}$	electron
elementary	●	•	•	●	$\mu^{\pm}$	muon
composite	●	•	●		$\pi^{\pm}$	pion
composite	●	•	●		$K^{\pm}$	kaon
composite		•	●		K_L^0	K-long
composite	●	•	●		$p/\overline{p}$	proton
composite		•	●		$n/\overline{n}$	neutron

Point Cloud

Collection of points in (position) space

[Popular Science, 2013]

Jet Formation Process



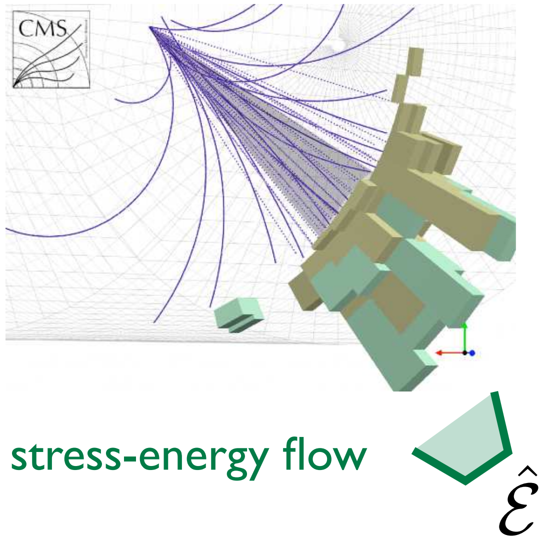
Stress-energy flow:

Robust to non-perturbative and detector effects

$$\boxed{\hat{\mathcal{E}} \simeq \lim_{t\to\infty} \hat{n}_i T^{0i}(t, vt\hat{n})}$$

[Sveshnikov, Tkachov, PLB 1996; Hofman, Maldacena, JHEP 2008; Mateu, Stewart, JDT, PRD 2013]

Jets as Weighted Point Clouds

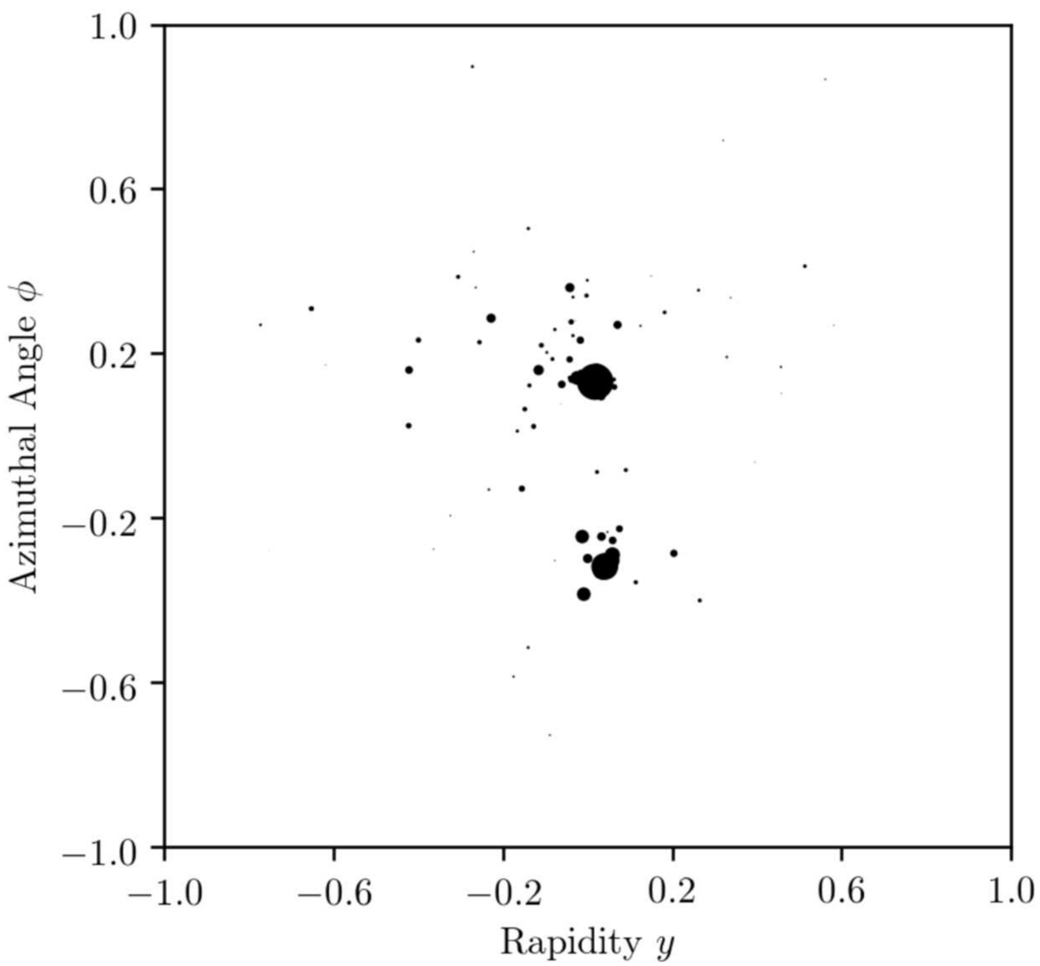


- Energy-weighted directions

$$\vec{p} = \{\underbrace{E}_{\text{Energy}}, \underbrace{\hat{n}_x, \hat{n}_y, \hat{n}_z}_{\text{Direction}}\}$$

- Visualize as Energy Density

$$\rho(\hat{n}) = \sum_{i \in \mathcal{J}} \underbrace{E_i}_{\text{Energy}} \, \delta^{(2)}(\hat{n} - \underbrace{\hat{n}_i}_{\text{Direction}})$$



- "Safe" to QCD singularities

"Thinking" Like a Physicist

Symmetry: $\mathcal{J} = \{\underbrace{\vec{p}_1, \vec{p}_2, \vec{p}_3, \ldots, \vec{p}_N}_{\text{Unordered, Variable Length Set}}\}$

Safety: $\vec{p} = \{E, \hat{n}_x, \hat{n}_y, \hat{n}_z\}$

Energy weighting

Properly specified problem

Many (labeled) examples $\{\mathcal{J}\}$

The Machine

Solution $S(\mathcal{J})$

Verification $V(\mathcal{J})$

Check that answer is physically sensible

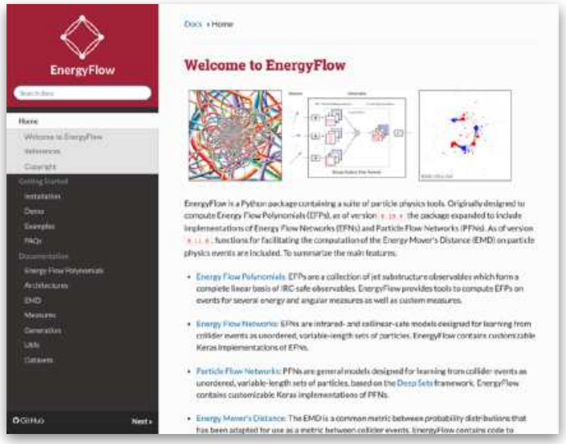

Patrick Komiske


Eric Metodiev

Theoretical
(High Energy)
Physics

?

Mathematics,
Statistics,
Computer Science

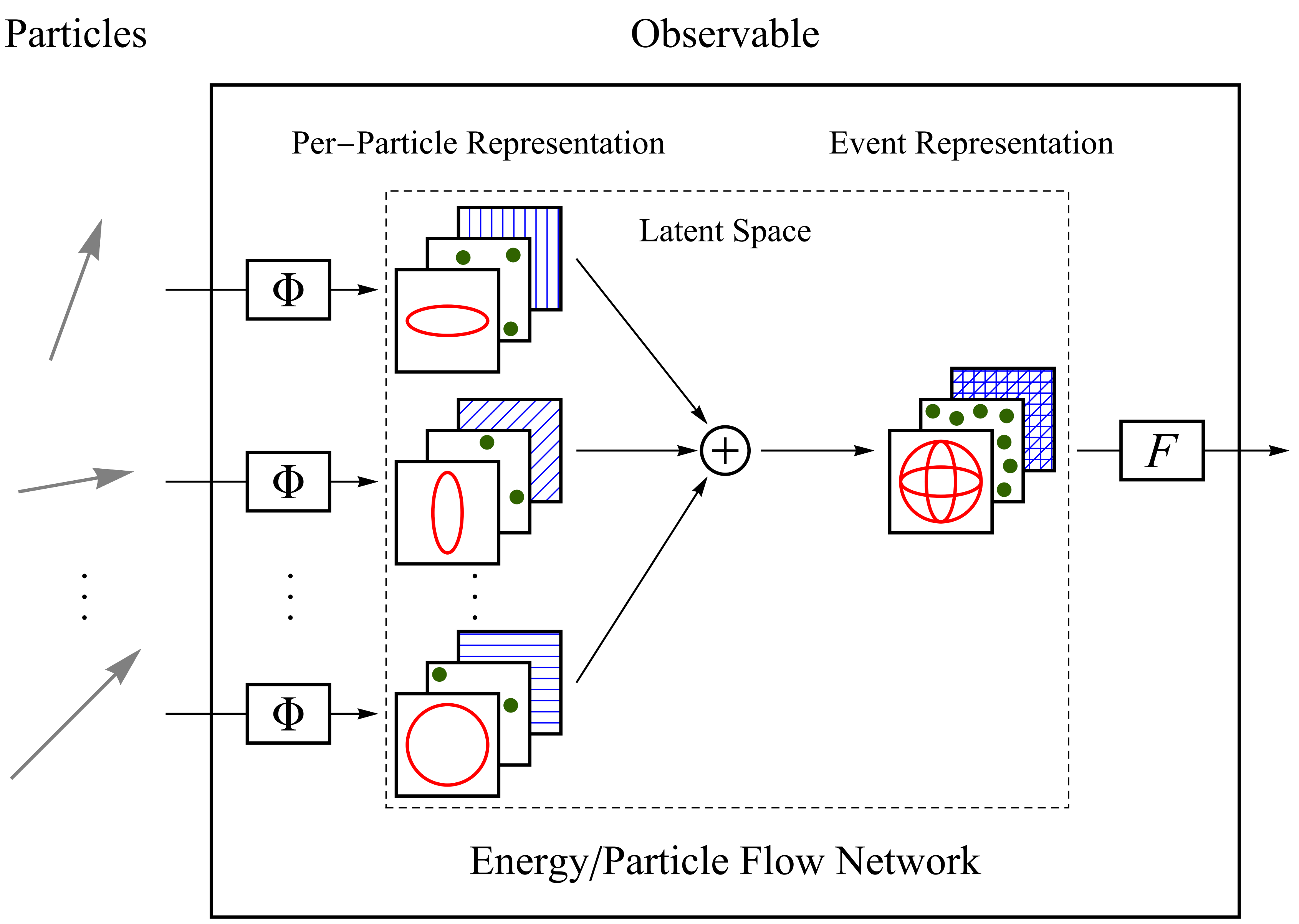


Energy Flow Networks

https://energyflow.network/

Energy Flow Networks

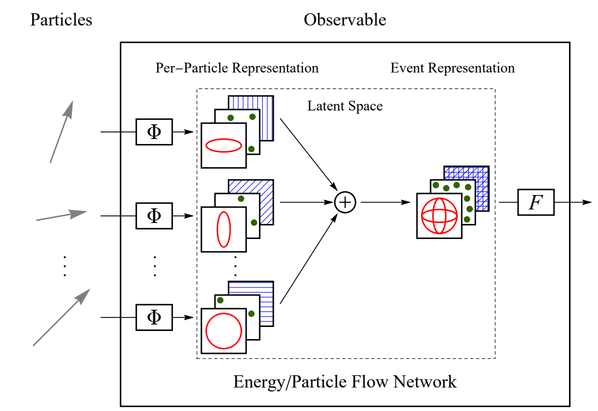
Architecture designed around symmetries and interpretability



[Komiske, Metodiev, JDT, JHEP 2019; see also Komiske, Metodiev, JDT, JHEP 2018;
special case of Zaheer, Kottur, Ravanbakhsh, Poczos, Salakhutdinov, Smola, NIPS 2017]

Energy Flow Networks

Architecture designed around symmetries and interpretability



Permutation invariant   Linear weights

$$S(\mathcal{J}) = F(V_1, V_2, \ldots, V_\ell) \qquad V_a(\mathcal{J}) = \sum_{i\in\mathcal{J}} E_i \, \Phi_a(\hat{n}_i)$$

Parametrized with Neural Networks

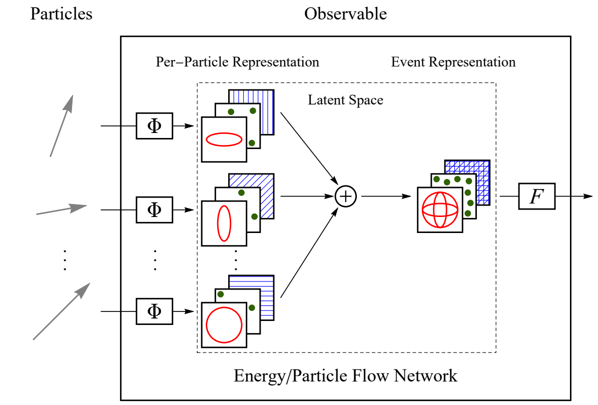
(see backup for details)

Provably describes any safe observable (!)*
Excellent jet classification performance
Intuitive visualization strategy

[Komiske, Metodiev, JDT, JHEP 2019; see also Komiske, Metodiev, JDT, JHEP 2018; special case of Zaheer, Kottur, Ravanbakhsh, Poczos, Salakhutdinov, Smola, NIPS 2017]

Energy Flow Networks

*Architecture designed around symmetries and **interpretability***

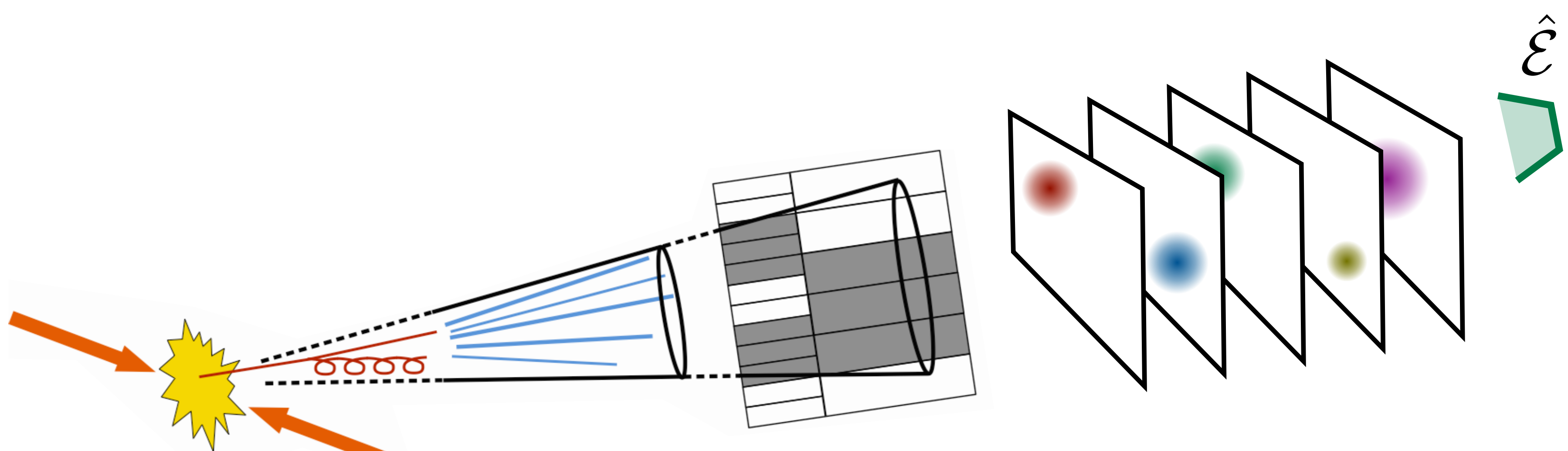


Latent space of dim ℓ

$$S(\mathcal{J}) = F\big(V_1, V_2, \ldots, V_\ell\big) \qquad V_a(\mathcal{J}) = \sum_{i \in \mathcal{J}} E_i \, \Phi_a(\hat{n}_i)$$

Can visualize if ℓ is small

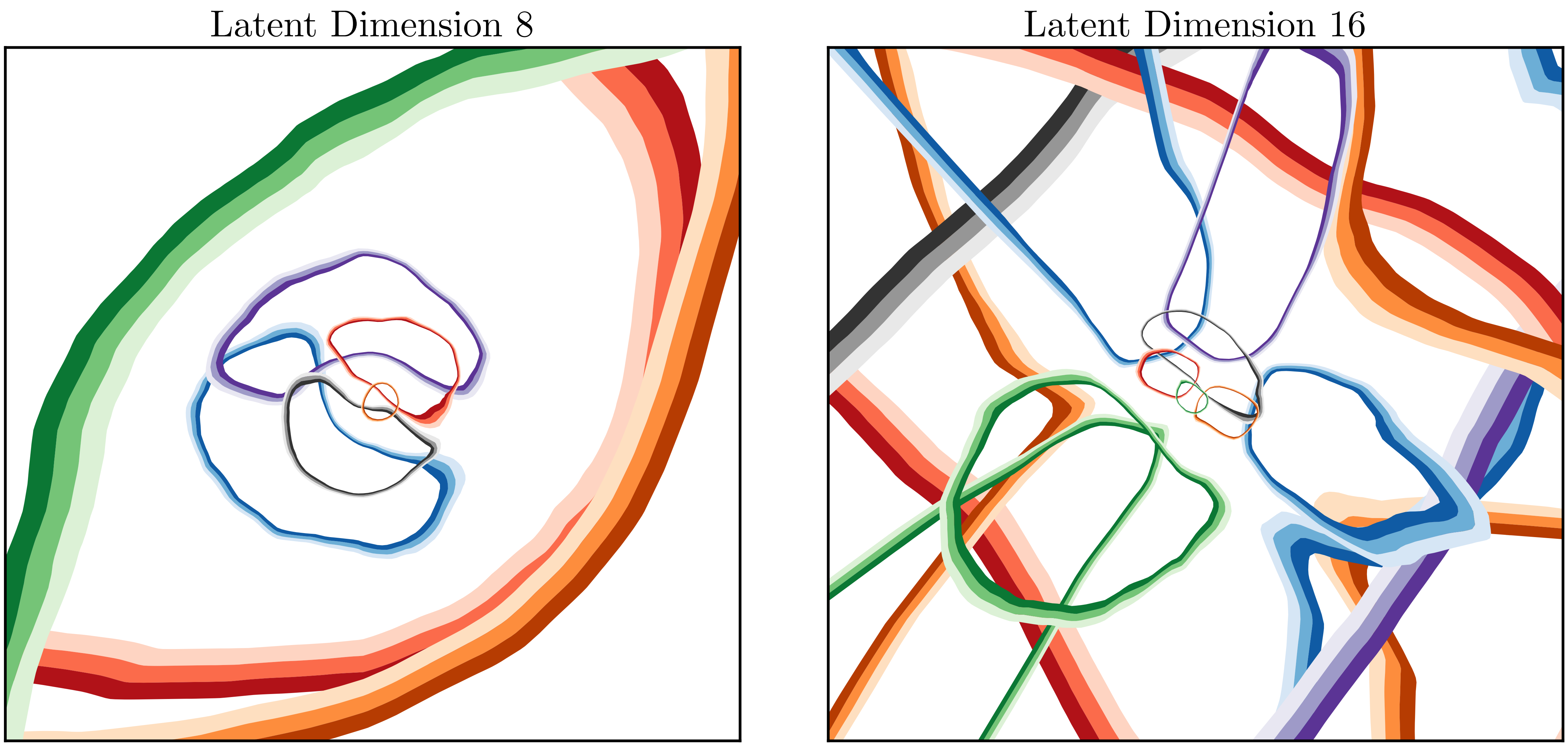
Easy to plot!



(similar to CNN filter activation)

[Komiske, Metodiev, JDT, JHEP 2019; see also Komiske, Metodiev, JDT, JHEP 2018; special case of Zaheer, Kottur, Ravanbakhsh, Poczos, Salakhutdinov, Smola, NIPS 2017]

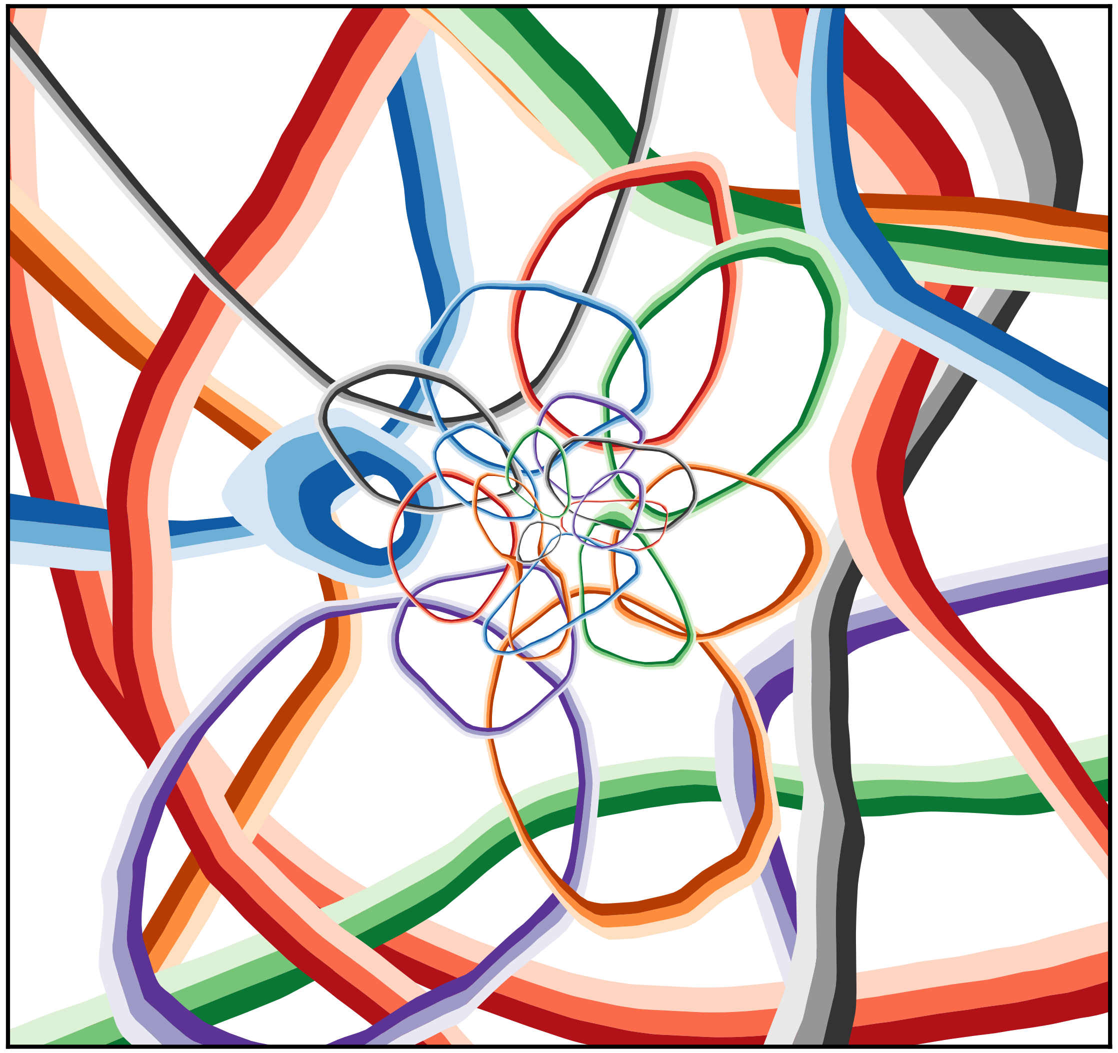
Psychedelic Network Visualization



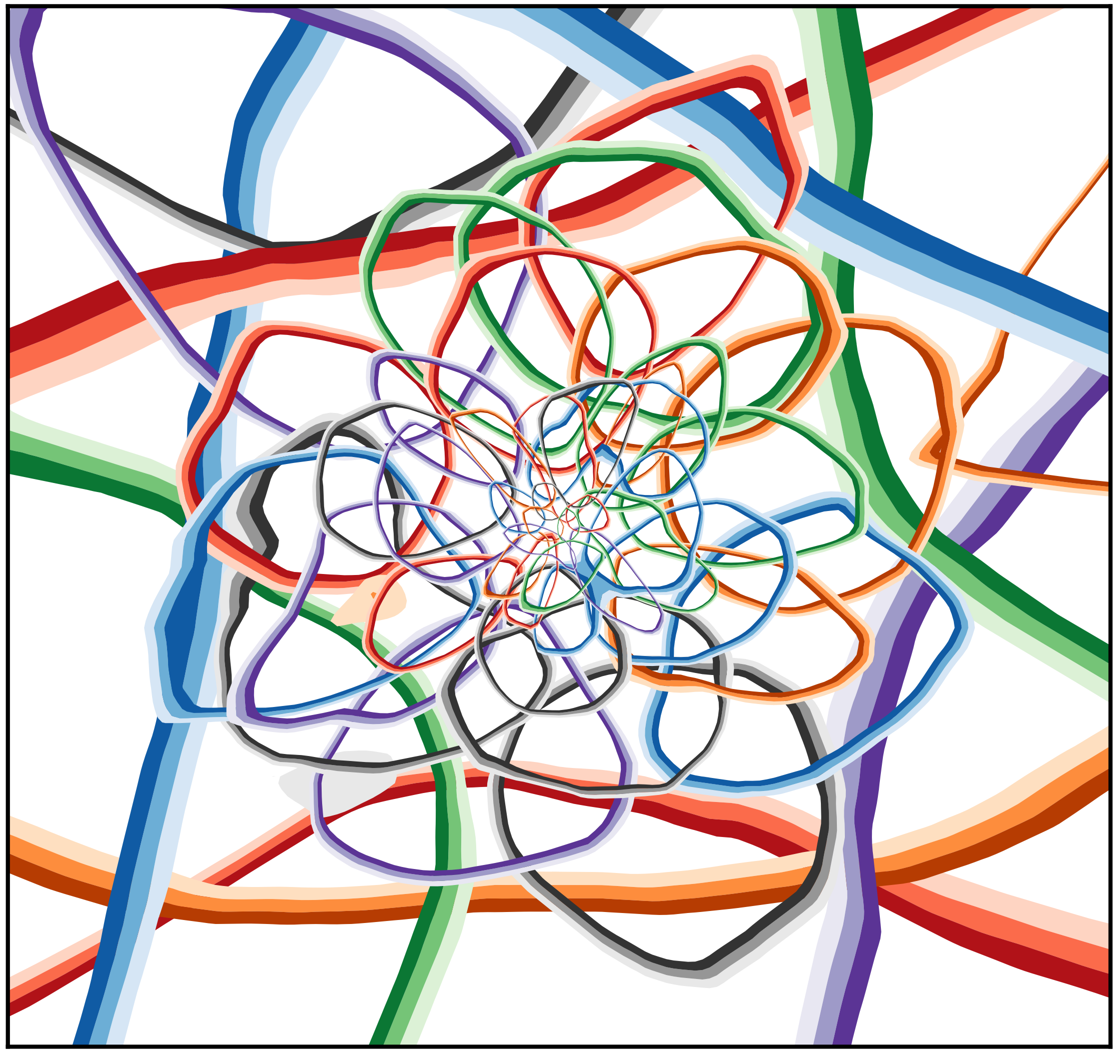
For the case of quark vs. gluon classification

Psychedelic Network Visualization

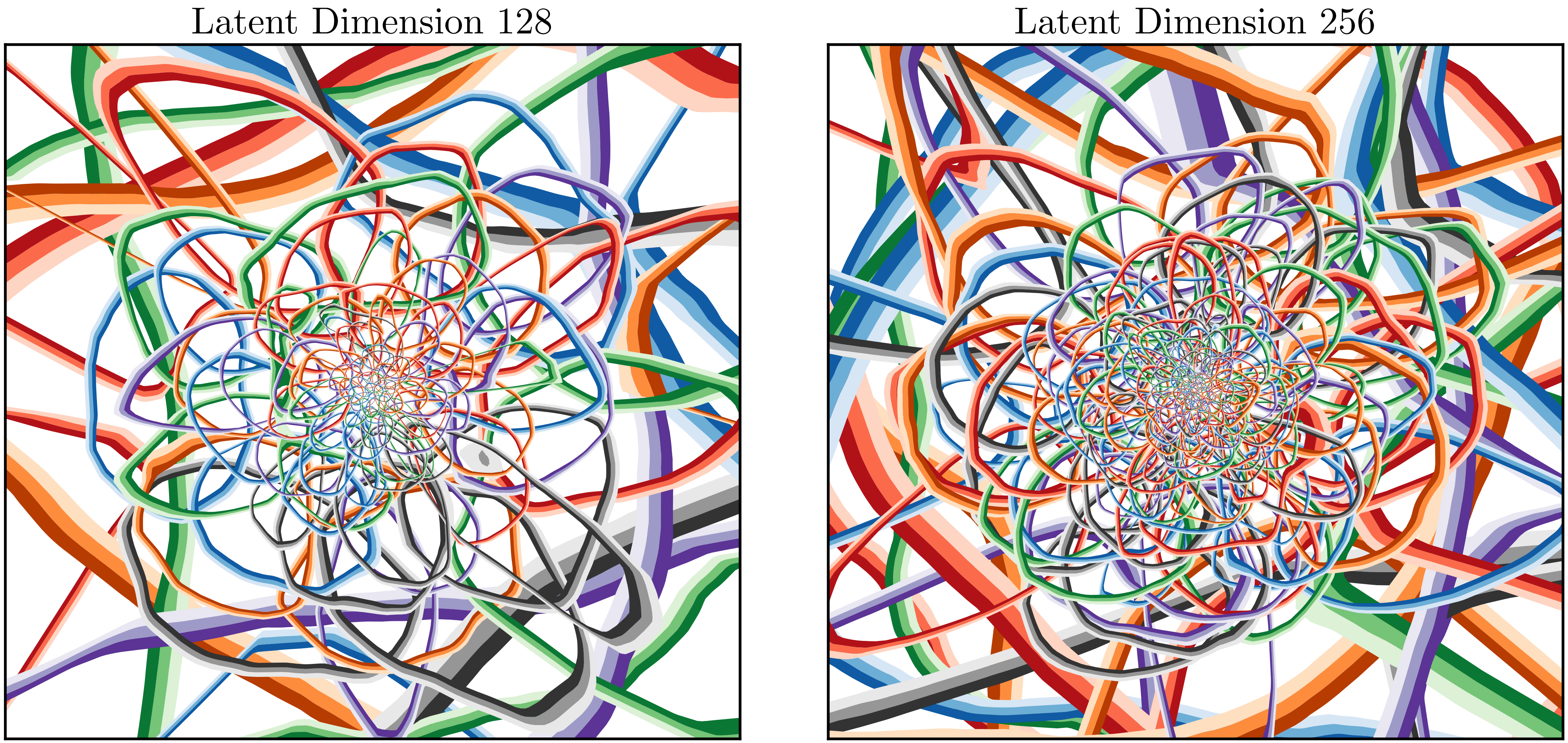
Latent Dimension 32



Latent Dimension 64

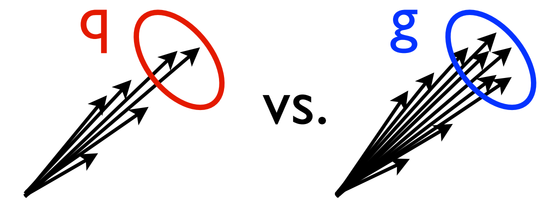


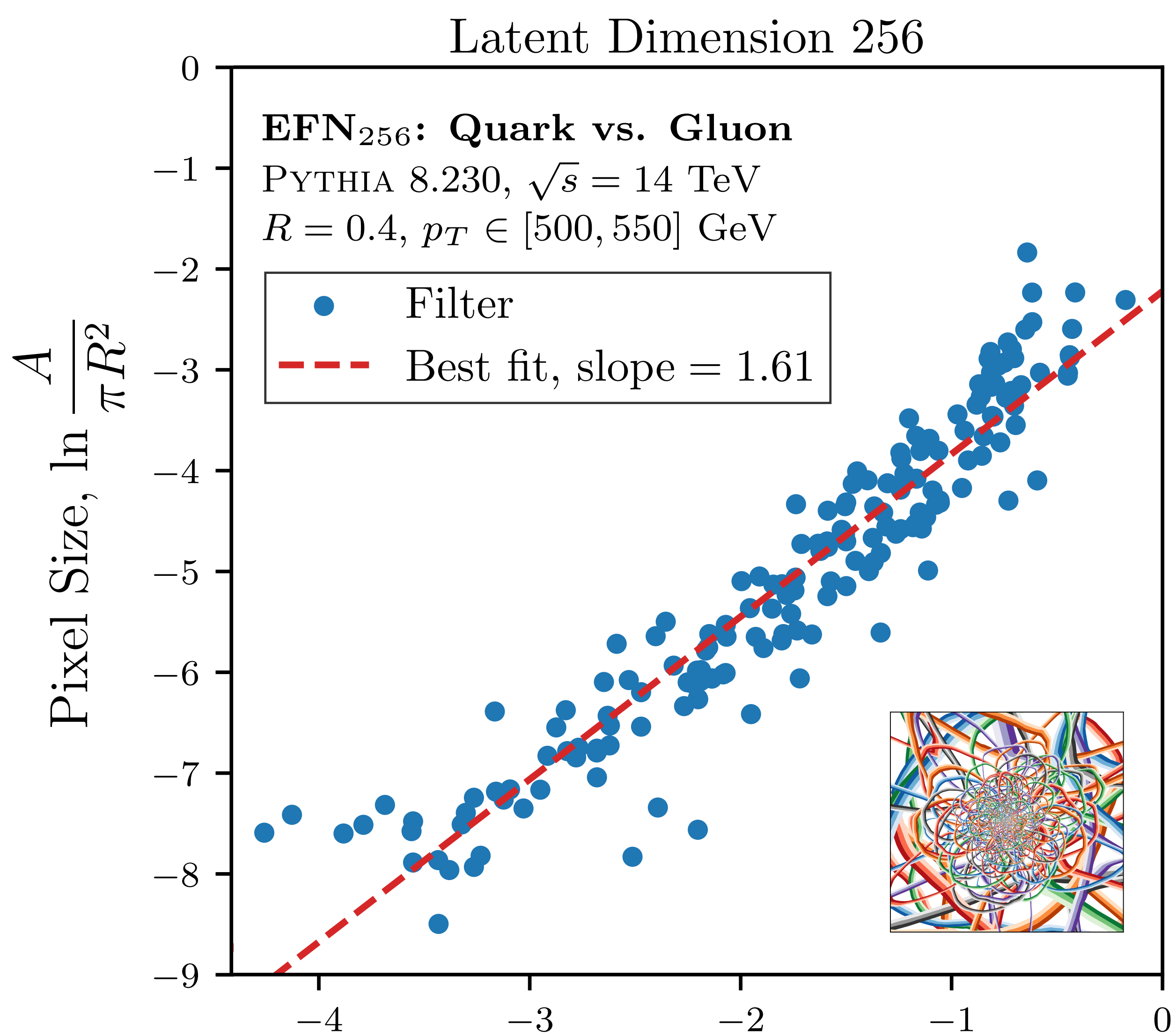
Psychedelic Network Visualization



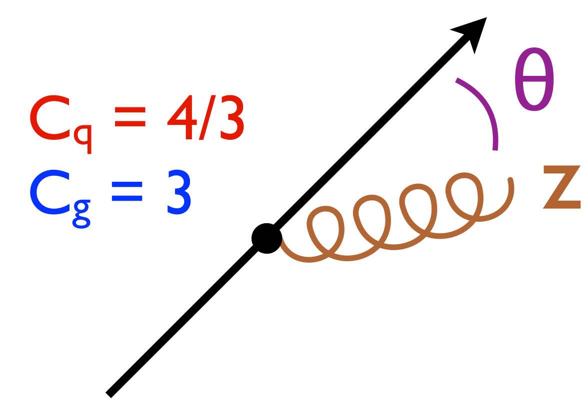
Singularity structure of QCD!

Putting the AI in AItarelli-Parisi





Radial Distance, $\ln \frac{\theta}{R}$

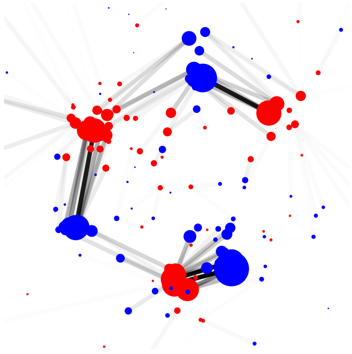


$$dP_{i \to ig} \simeq \frac{2\alpha_s}{\pi} C_i \underbrace{\frac{d\theta}{\theta}}_{\text{Collinear}} \underbrace{\frac{dz}{z}}_{\text{Soft}}$$

[Komiske, Metodiev, JDT, JHEP 2019]

Scenes from My Sabbatical

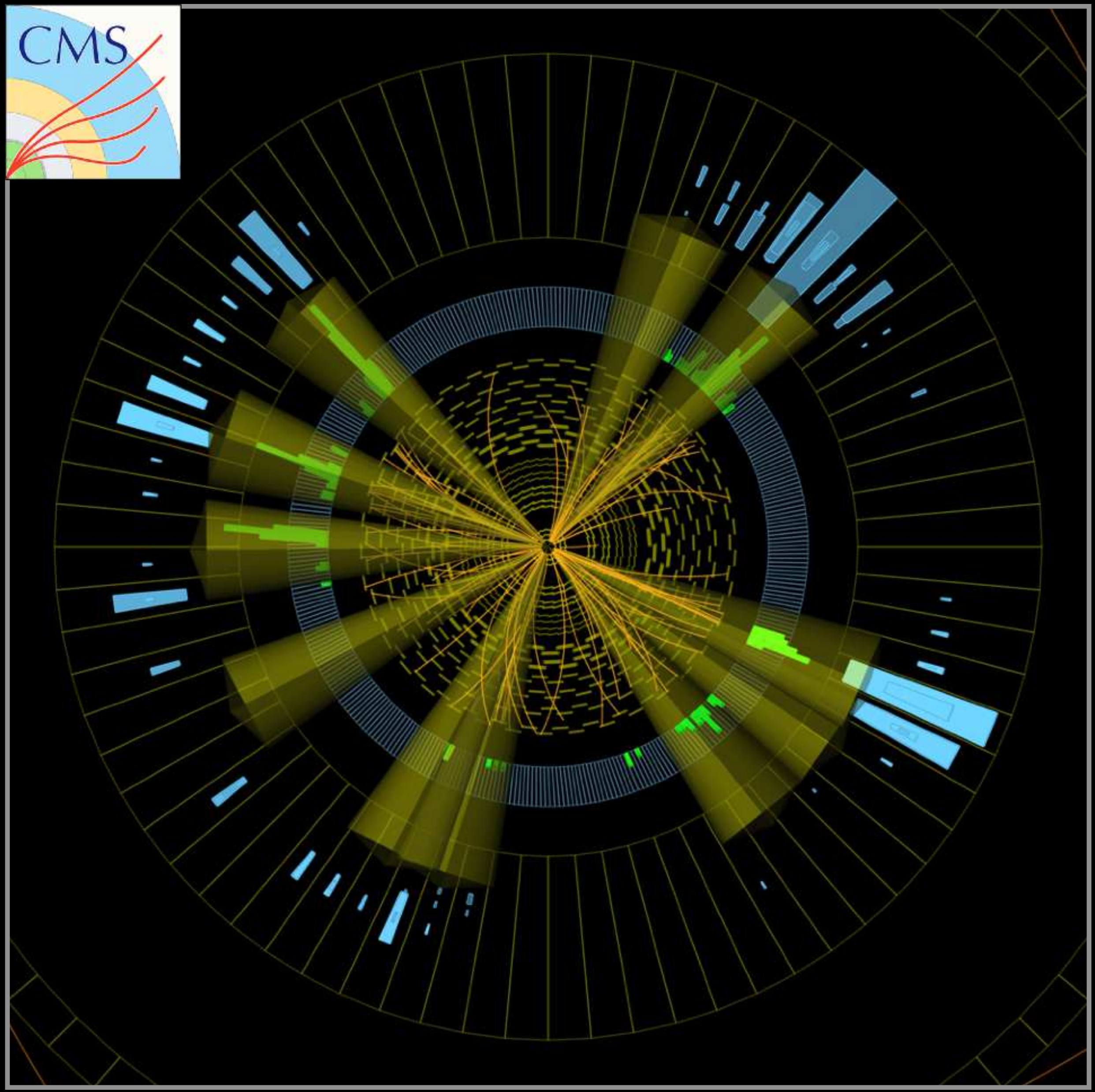
What is a Collider Event?

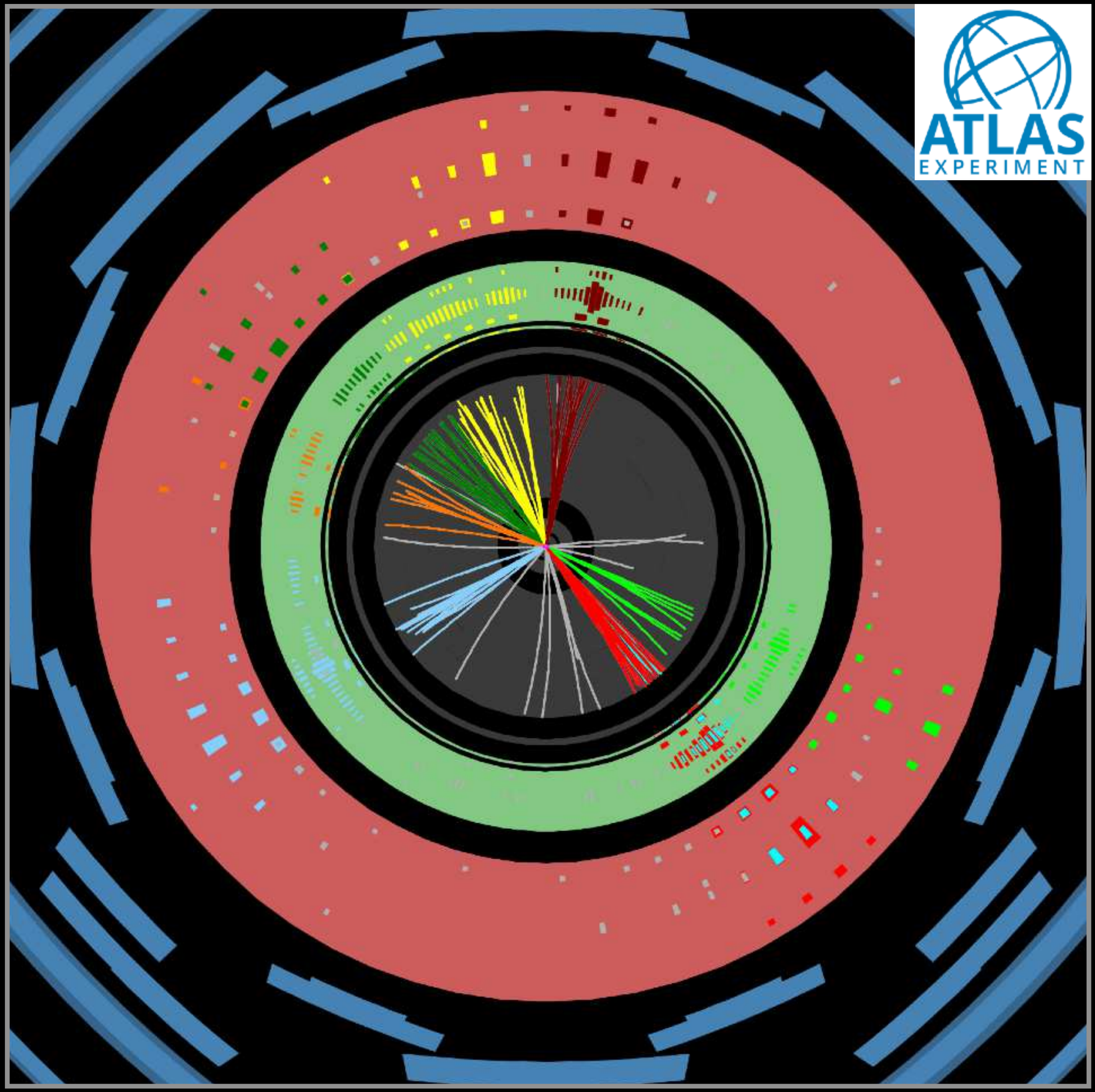


When are Collider Events Similar?

Two Collider Events

Two collections of points in (momentum) space

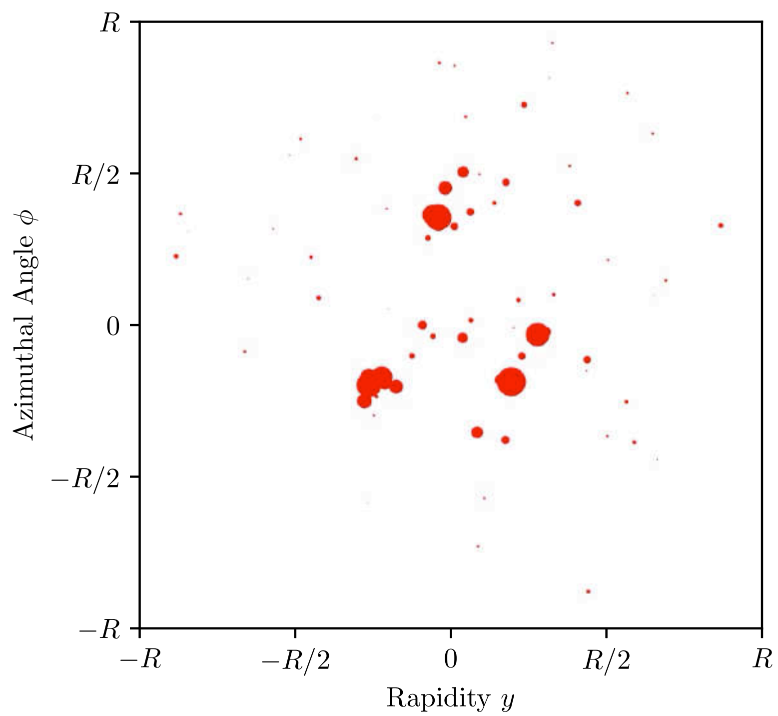




How "close" are these? (8.5 km?)

Similarity of Two Energy Flows?

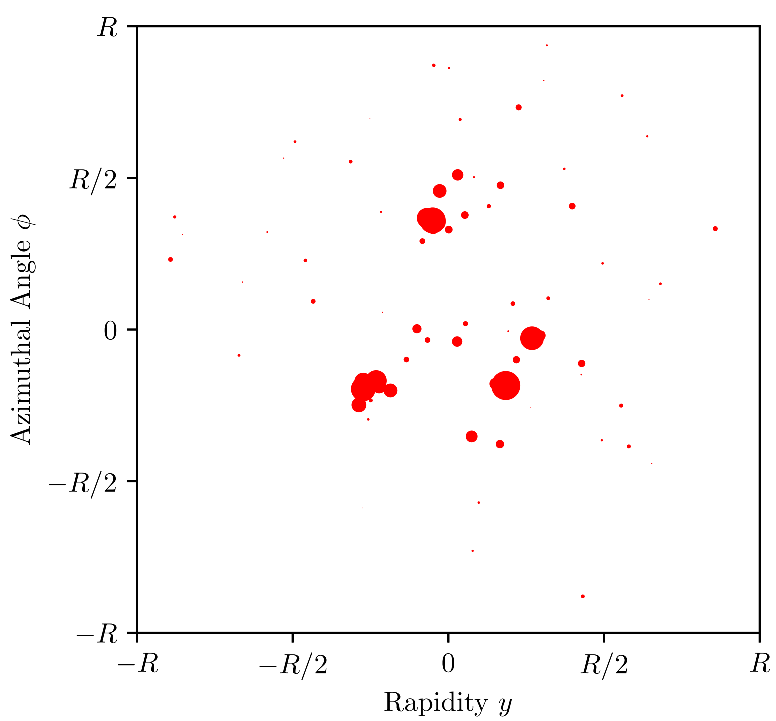
$$\rho(\hat{n}) = \sum_{i \in \mathcal{J}} E_i \, \delta^{(2)}(\hat{n} - \hat{n}_i)$$

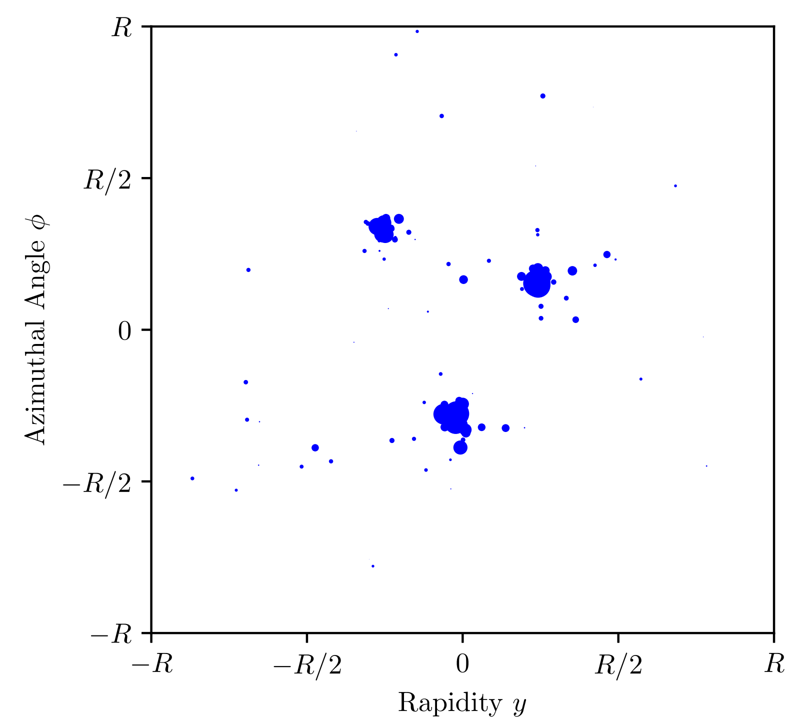


Optimal Transport:

Earth Mover's Distance
a.k.a. 1-Wasserstein metric

[Peleg, Werman, Rom, IEEE 1989;
Rubner, Tomasi, Guibas, ICCV 1998, ICJV 2000;
Pele, Werman, ECCV 2008; Pele Taskar, GSI 2013]

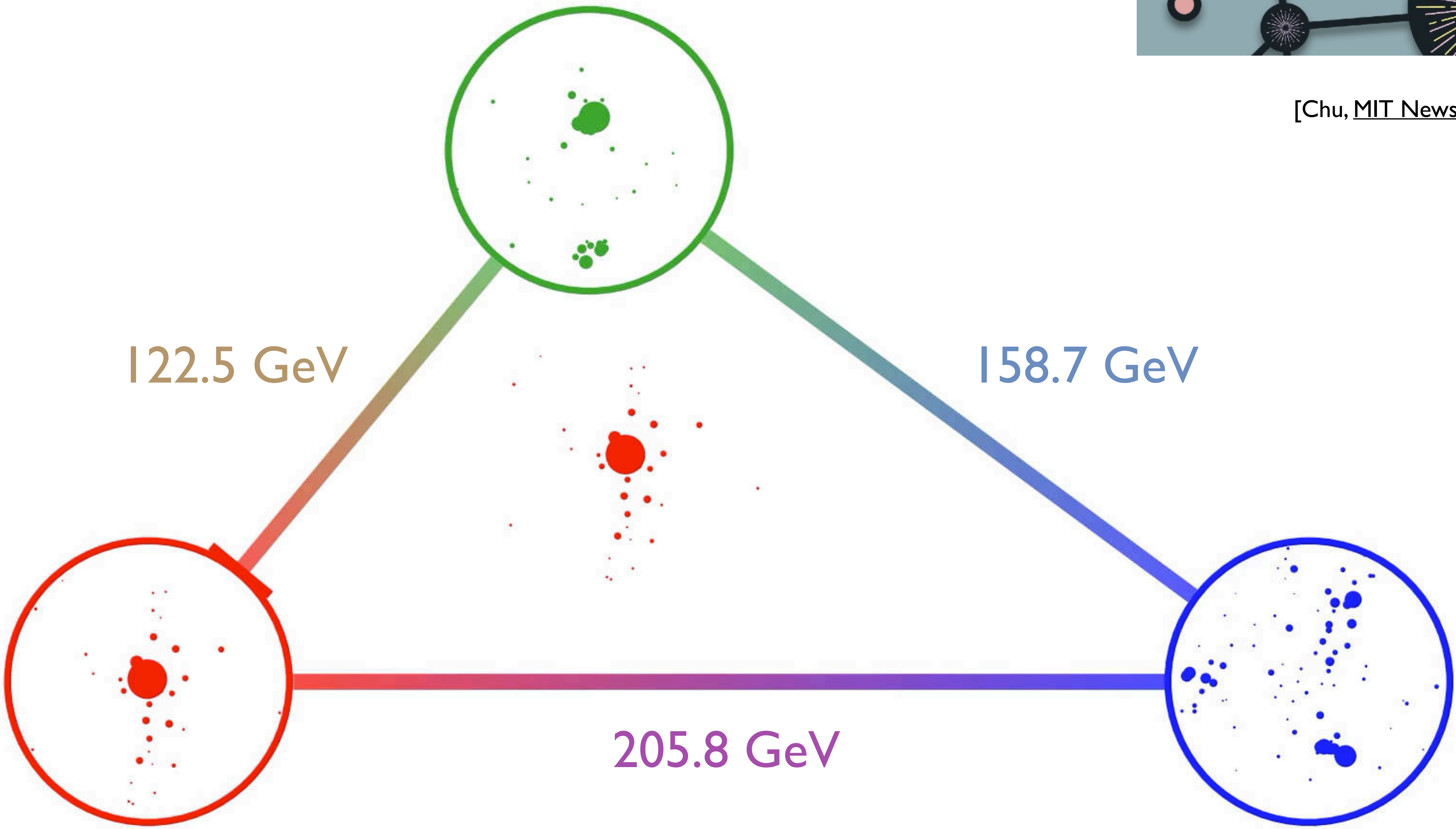




[Komiske, Metodiev, JDT, PRL 2019; code at Komiske, Metodiev, JDT, energyflow.network]

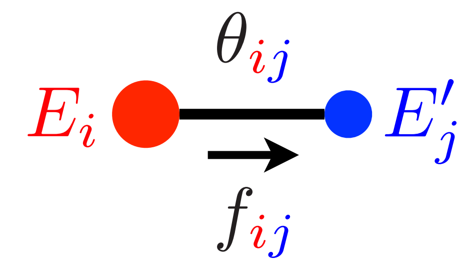
Similarity of Three Energy Flows?

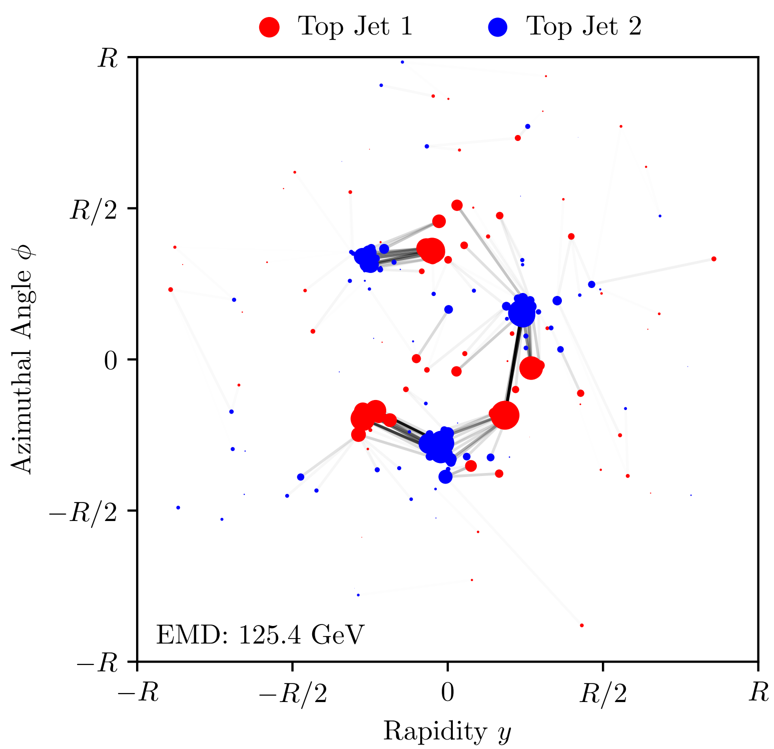
[Chu, MIT News July 2019]



[Komiske, Metodiev, JDT, PRL 2019; code at Komiske, Metodiev, JDT, energyflow.network]

The Energy Mover's Distance

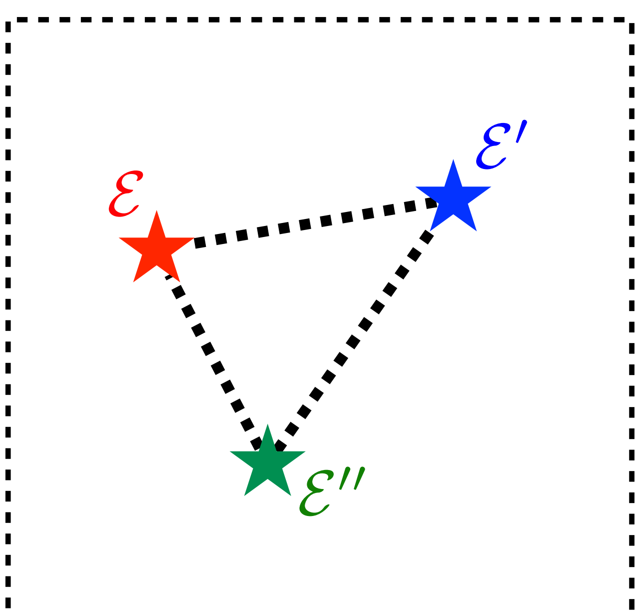




Optimal transport between energy flows…

$$\mathrm{EMD}(\mathcal{E},\mathcal{E}') = \underbrace{\min_{\{f\}} \sum_i \sum_j f_{ij} \frac{\theta_{ij}}{R}}_{\text{Cost to move energy}} + \underbrace{\left| \sum_i E_i - \sum_j E'_j \right|}_{\text{Cost to create energy}}$$

in GeV



…defines a metric on the space of events

$$0 \le \mathrm{EMD}(\mathcal{E},\mathcal{E}') \le \mathrm{EMD}(\mathcal{E},\mathcal{E}'') + \mathrm{EMD}(\mathcal{E}',\mathcal{E}'')$$

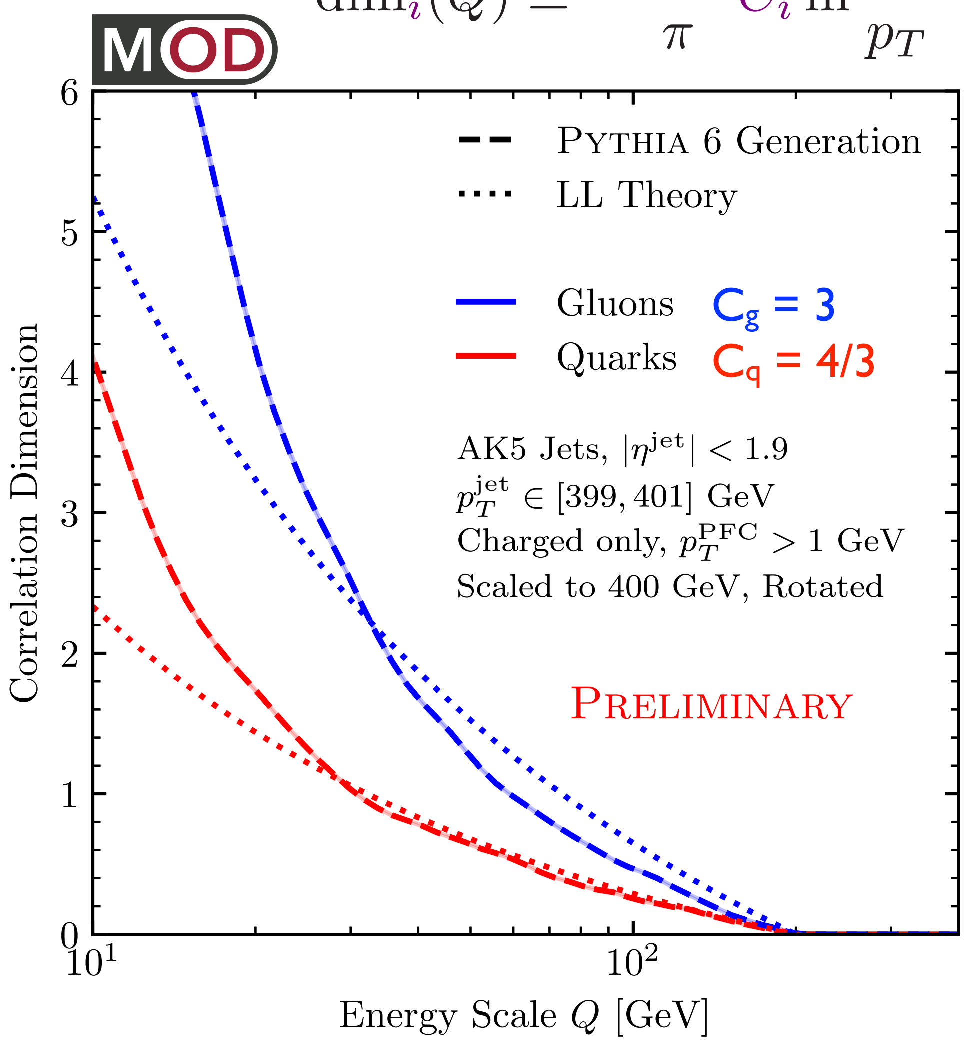
(assuming R ≥ $\theta_{max}/2$, i.e. R ≥ jet radius for conical jets)

[Komiske, Metodiev, JDT, PRL 2019; see also Pele, Werman, ECCV 2008; Pele, Taskar, GSI 2013]

Dimensionality of Space of Jets

QCD Calculation

$$\dim_i(Q) \simeq -\frac{8\alpha_s}{\pi} C_i \ln \frac{Q}{p_T}$$

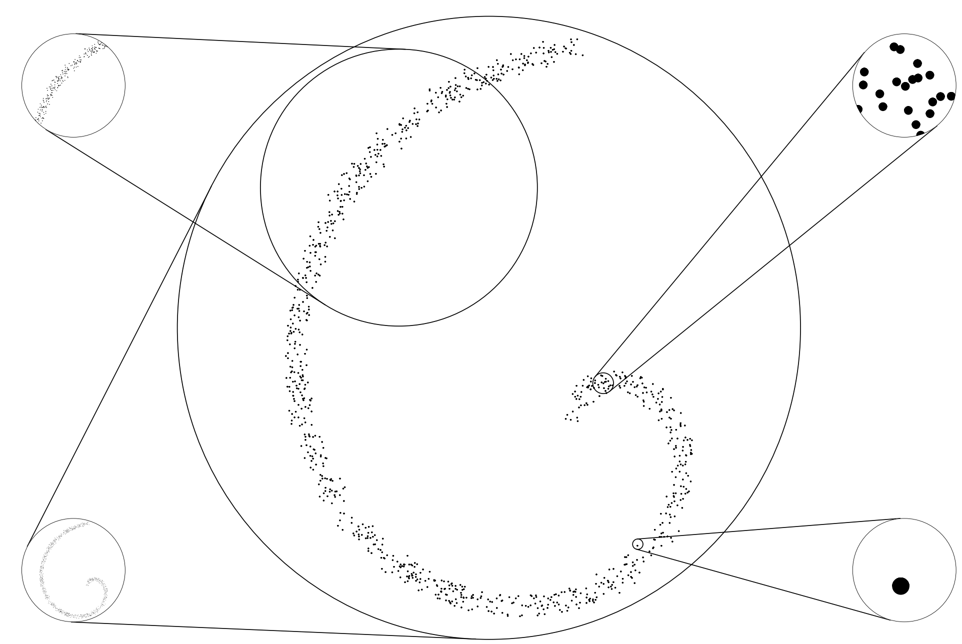


$$N_{\text{neighbors}}(r) \sim r^{\dim}$$

$$\Rightarrow \quad \dim(r) \sim r \frac{\partial}{\partial r} \ln N_{\text{neighbors}}(r)$$

dim≃1

dim≃2



dim≃2

(eventually 0)

dim≃0

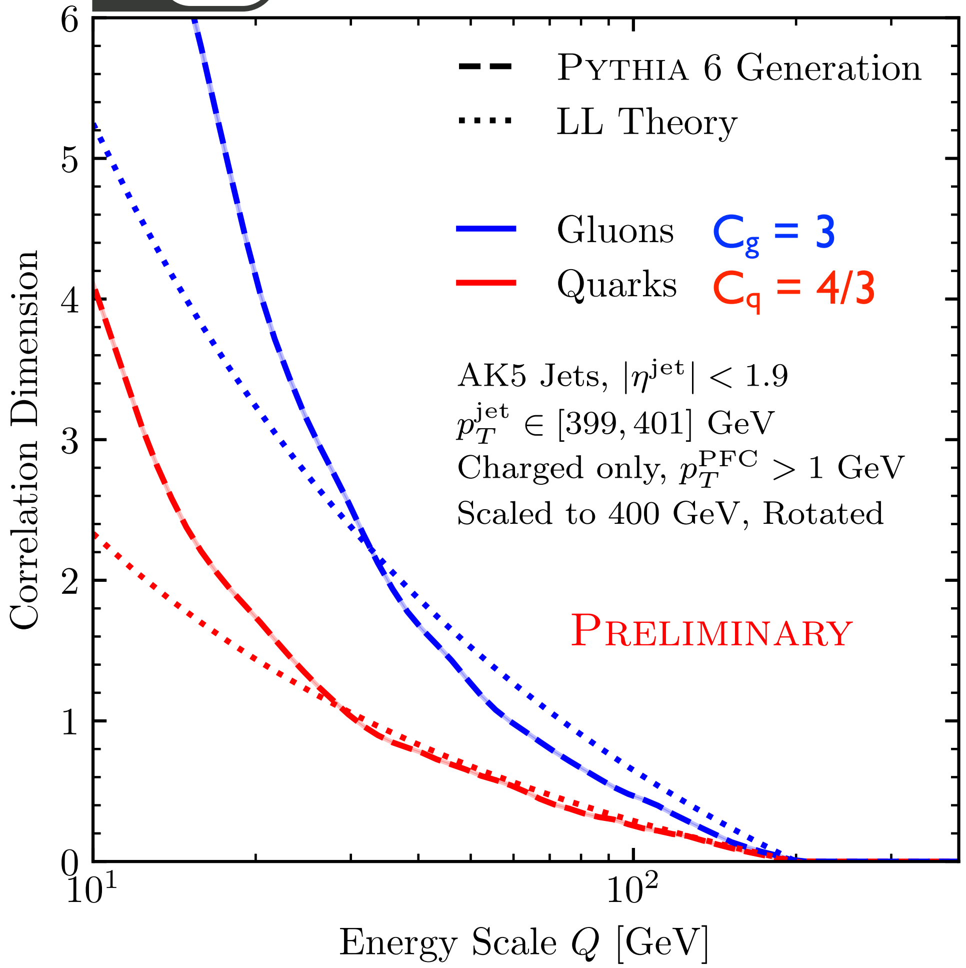
[Grassberger, Procaccia, PRL 1983; Kégl, NIPS 2002]

Dimensionality of Space of Jets

[http://opendata.cern.ch/]

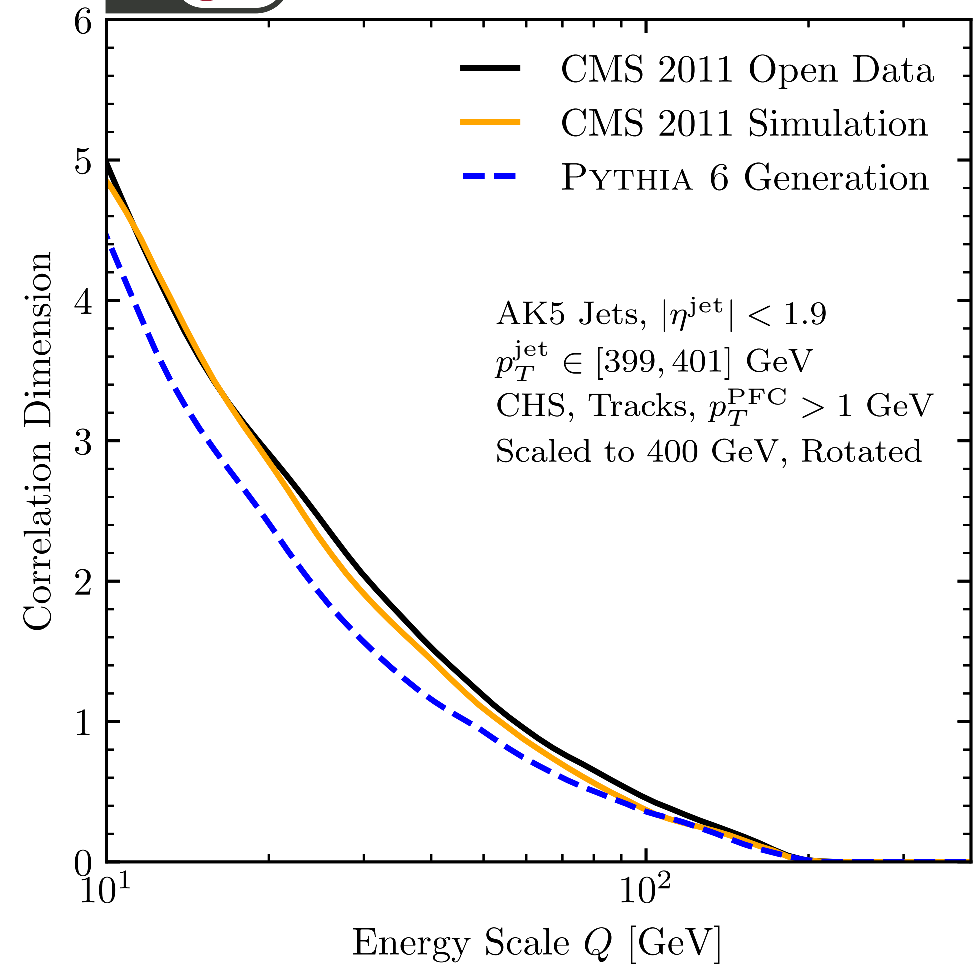
QCD Calculation

$$\dim_i(Q) \simeq -\frac{8\alpha_s}{\pi} C_i \ln \frac{Q}{p_T}$$



CMS Open Data

400 GeV jets in 2.3 fb^{-1} of 7 TeV pp collisions

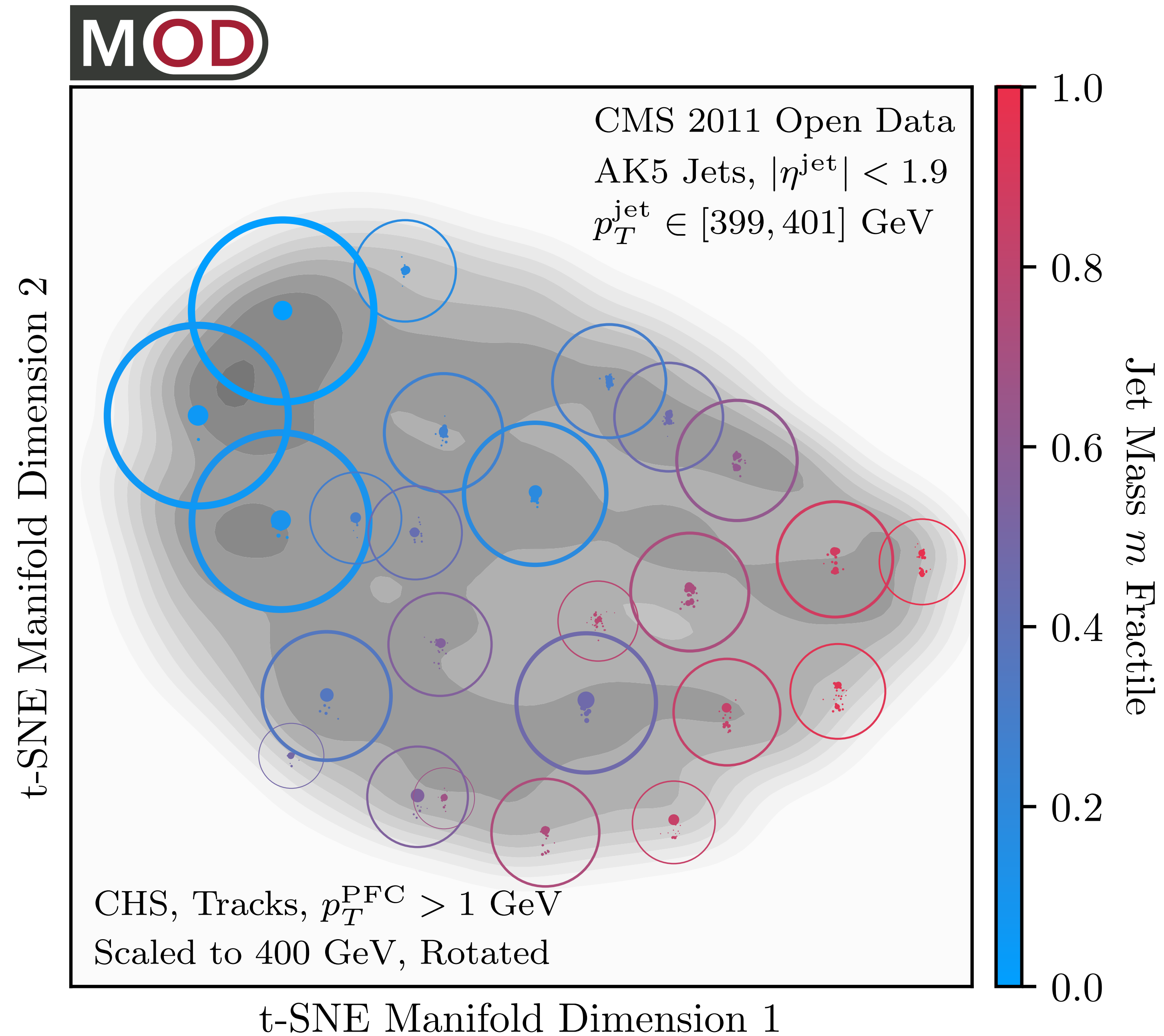


[Komiske, Mastandrea, Metodiev, Naik, JDT, submitted to PRD]



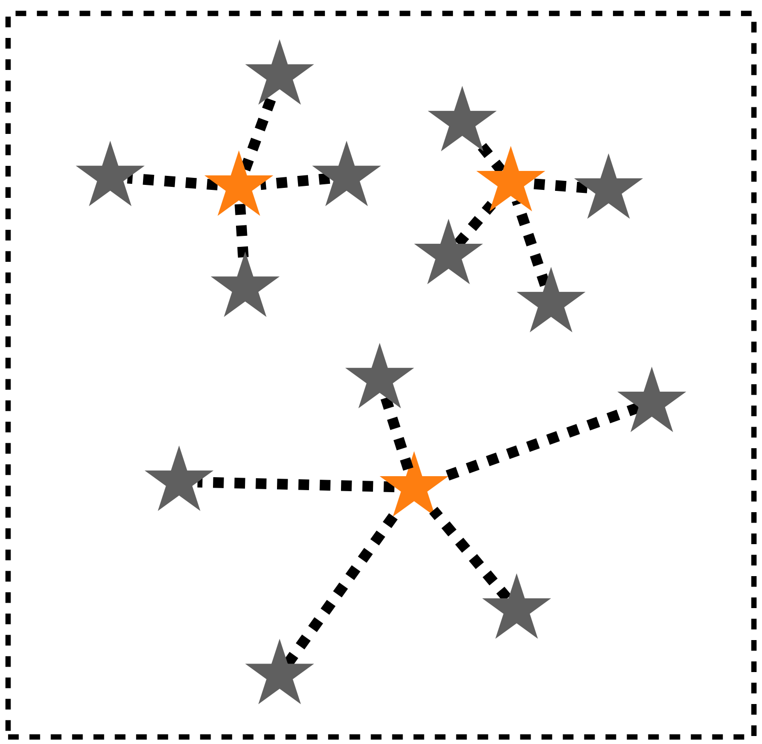

Most Representative Jets

[http://opendata.cern.ch/]



k-medoids

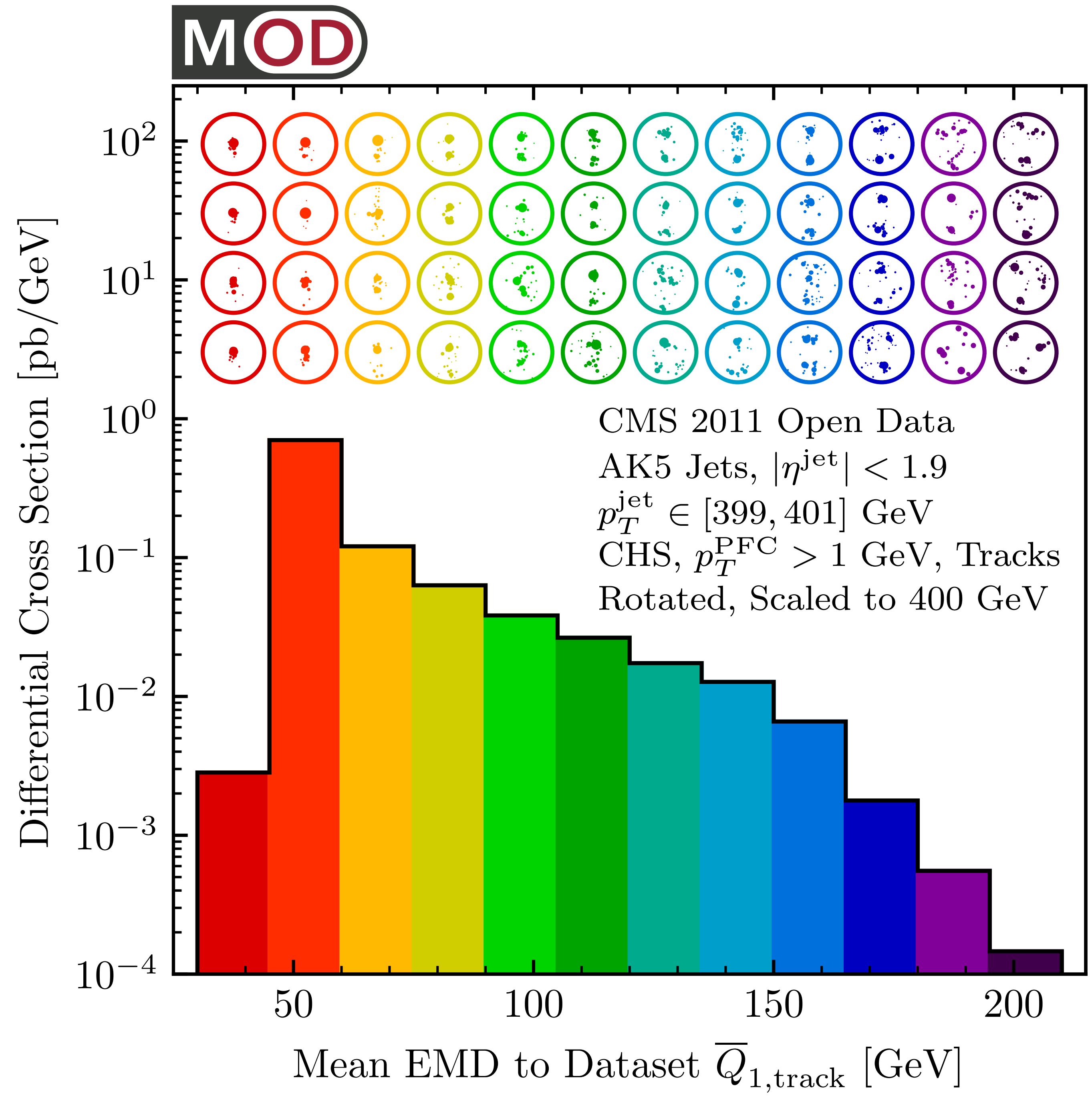
Arranged via t-SNE



[Komiske, Mastandrea, Metodiev, Naik, JDT, submitted to PRD; using van der Maaten, Hinton, JMLR 2008]

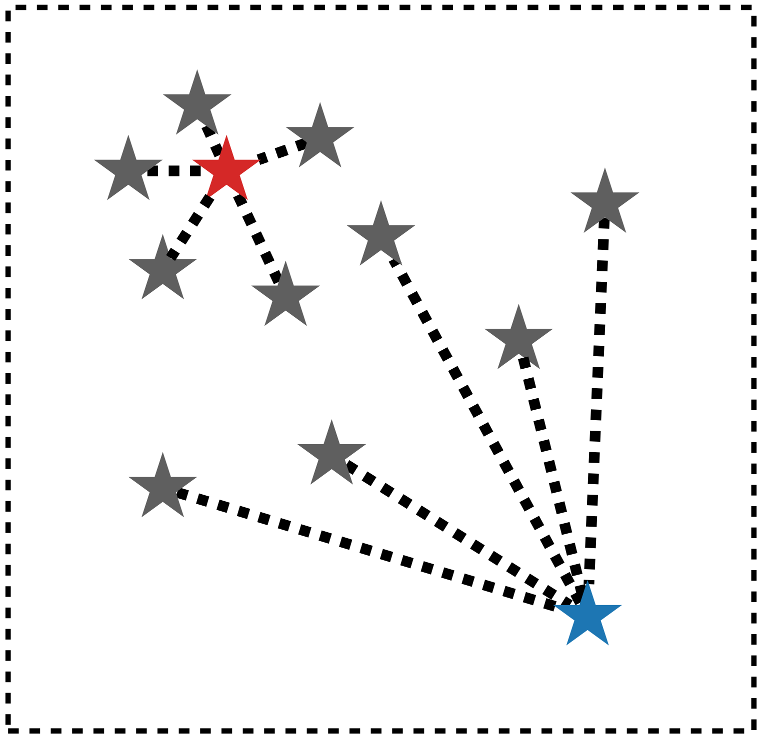
Least Representative Jets

[http://opendata.cern.ch/]



New Physics?

Or tails of QCD?



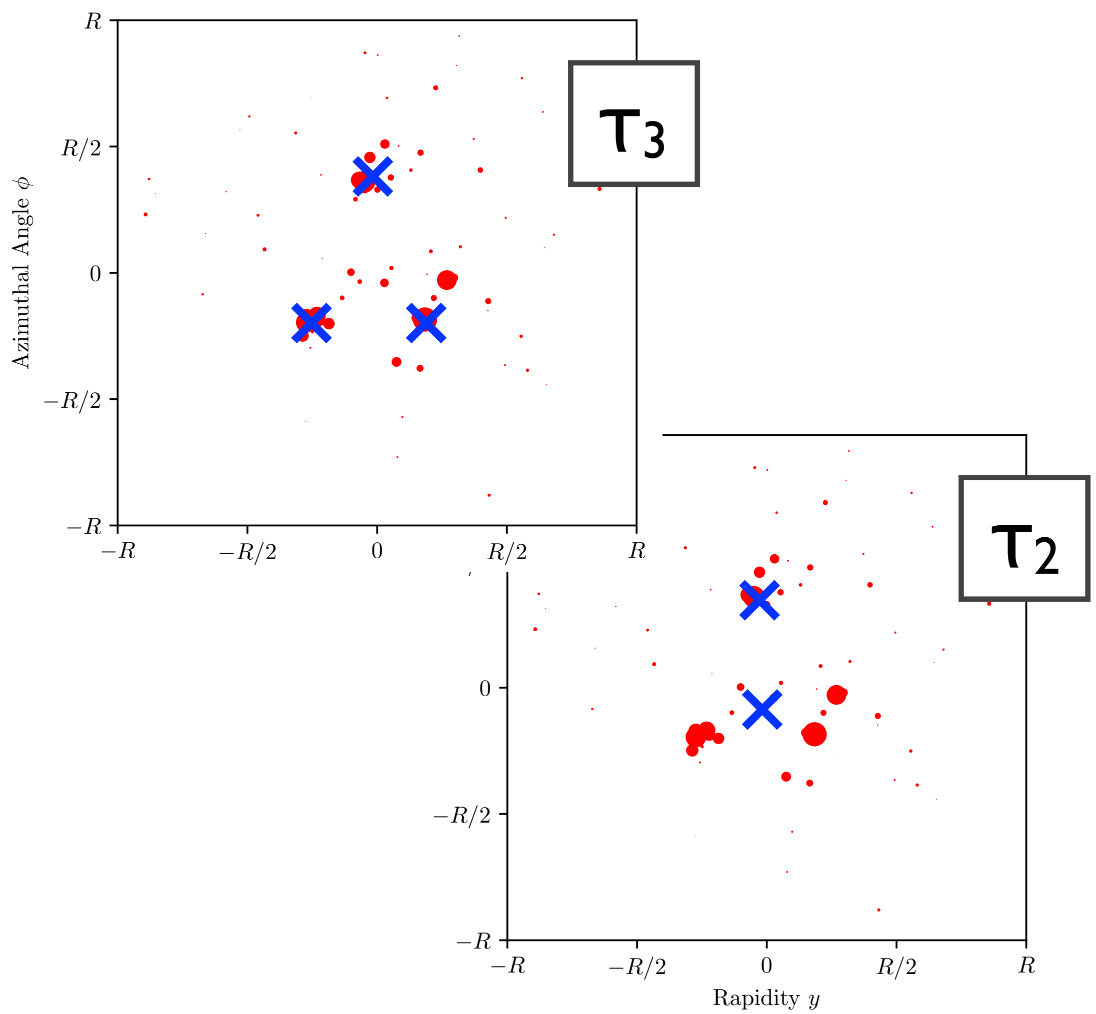
[Komiske, Mastandrea, Metodiev, Naik, JDT, submitted to PRD]

N-subjettiness

Ubiquitous jet substructure observable used for almost a decade…

$$\tau_N(\mathcal{E}) = \min_{N\text{ axes}} \sum_i E_i \min\left\{\theta_{1,i}, \theta_{2,i}, \ldots, \theta_{N,i}\right\}$$

IRC safe



[JDT, Van Tilburg, JHEP 2011, JHEP 2012;
based on Brandt, Dahmen, ZPC 1979; Stewart, Tackmann, Waalewijn, PRL 2010]

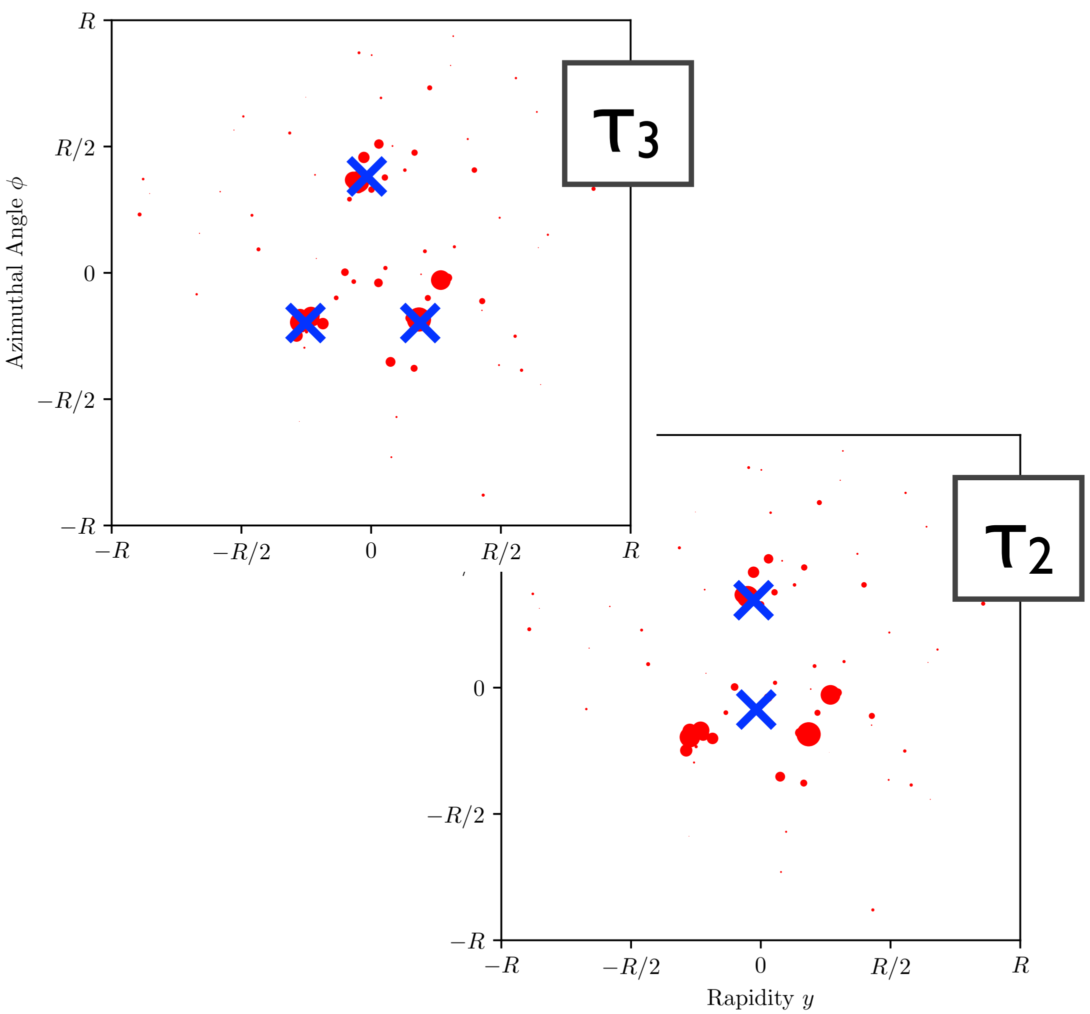
N-subjettiness = Point to Manifold EMD

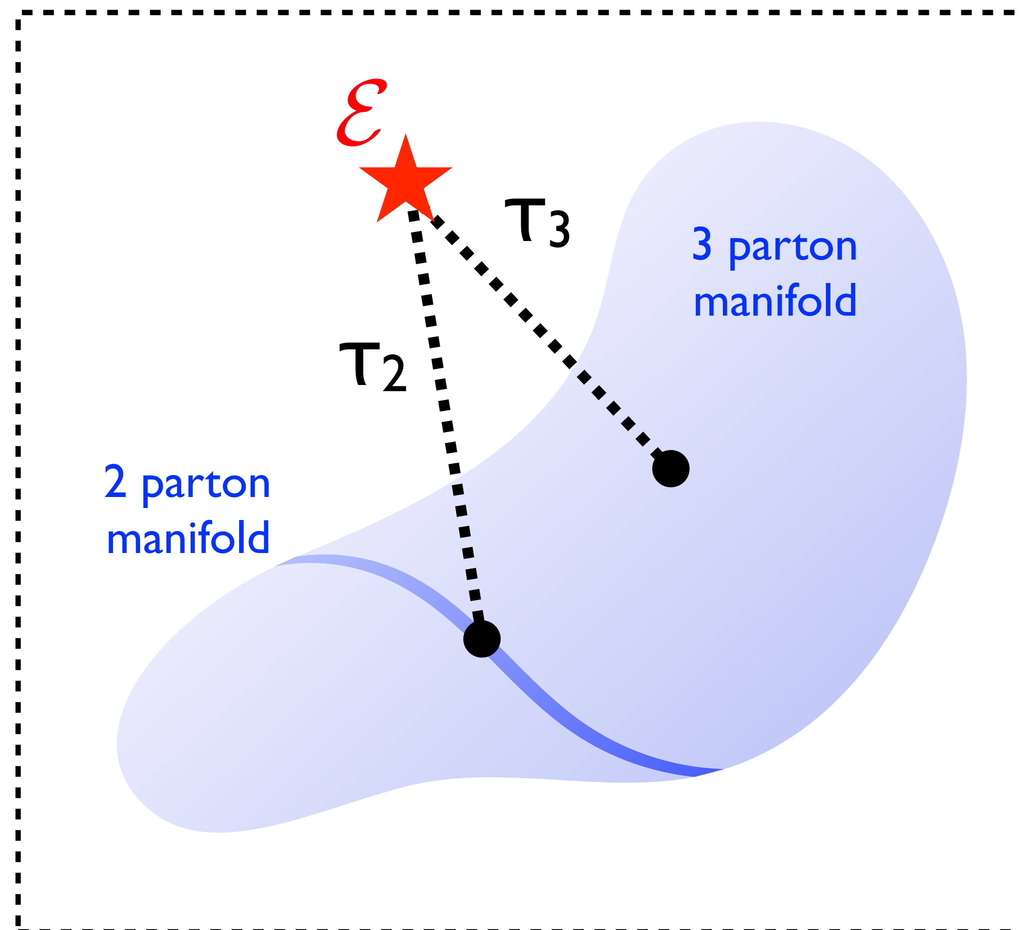
…is secretly an optimal transport problem

$$\tau_N(\mathcal{E}) = \min_{|\mathcal{E}'|=N} \mathrm{EMD}(\mathcal{E}, \mathcal{E}')$$

IRC safe

(!)



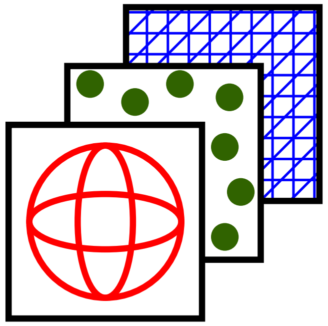


[JDT, Van Tilburg, JHEP 2011, JHEP 2012;
rephrased in the language of Komiske, Metodiev, JDT, PRL 2019]

Summary

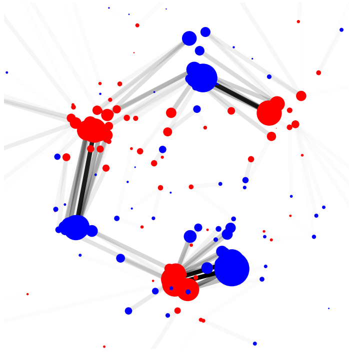
Scenes from My Sabbatical

(Great to be home!)
Machine learning offers powerful tools to analyze collision debris



What is a Collider Event?

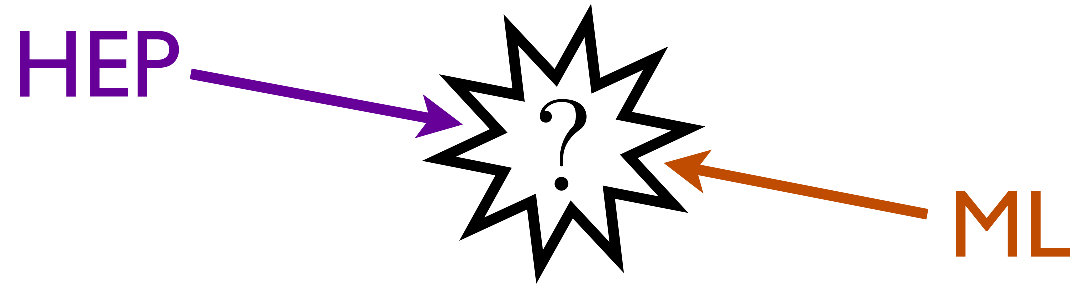
Unordered set of particles describing energy flow of jets
Inspires network architectures designed for symmetry and safety



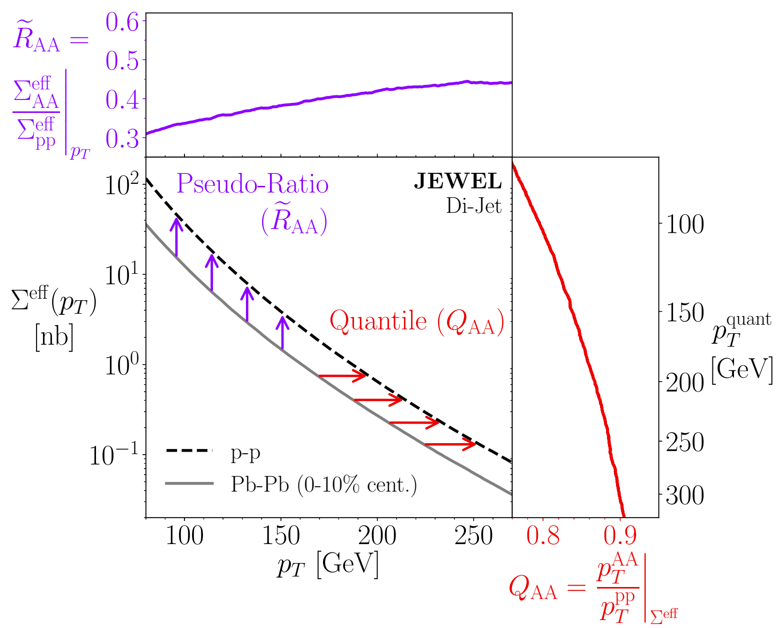
When are Collider Events Similar?

When their energy flows are similar
Inspires unsupervised learning strategies based on event geometry

More Collisions

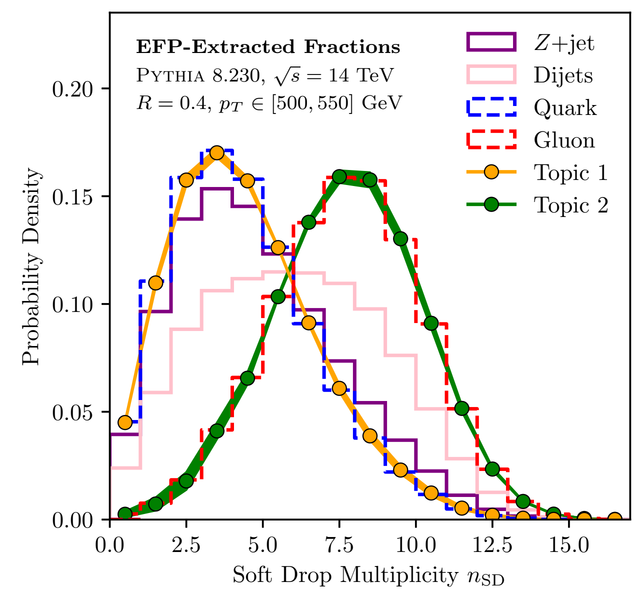


Jet Quenching
via **Optimal Transport**



[Brewer, Milhano, JDT, PRL 2019]

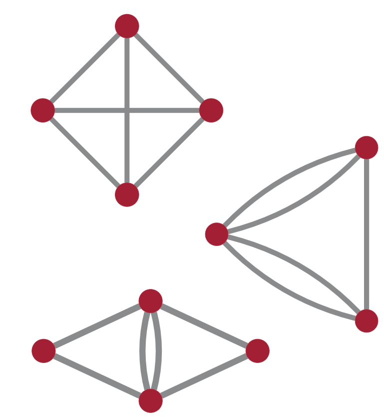
Unsupervised Jet Classification
via **Blind Source Separation**



[Komiske, Metodiev, JDT, JHEP 2018]

Kinematic Decomposition
via **Graph Theory**

	Leafless Multigraphs	
	Connected	All
Edges d	A307317	A307316
1	0	0
2	1	1
3	2	2
4	4	5
5	9	11
6	26	34
7	68	87
8	217	279
9	**718**	**897**
10	**2 553**	**3 129**
11	**9 574**	**11 458**
12	**38 005**	**44 576**
13	**157 306**	**181 071**
14	**679 682**	**770 237**
15	**3 047 699**	**3 407 332**
16	**14 150 278**	**15 641 159**

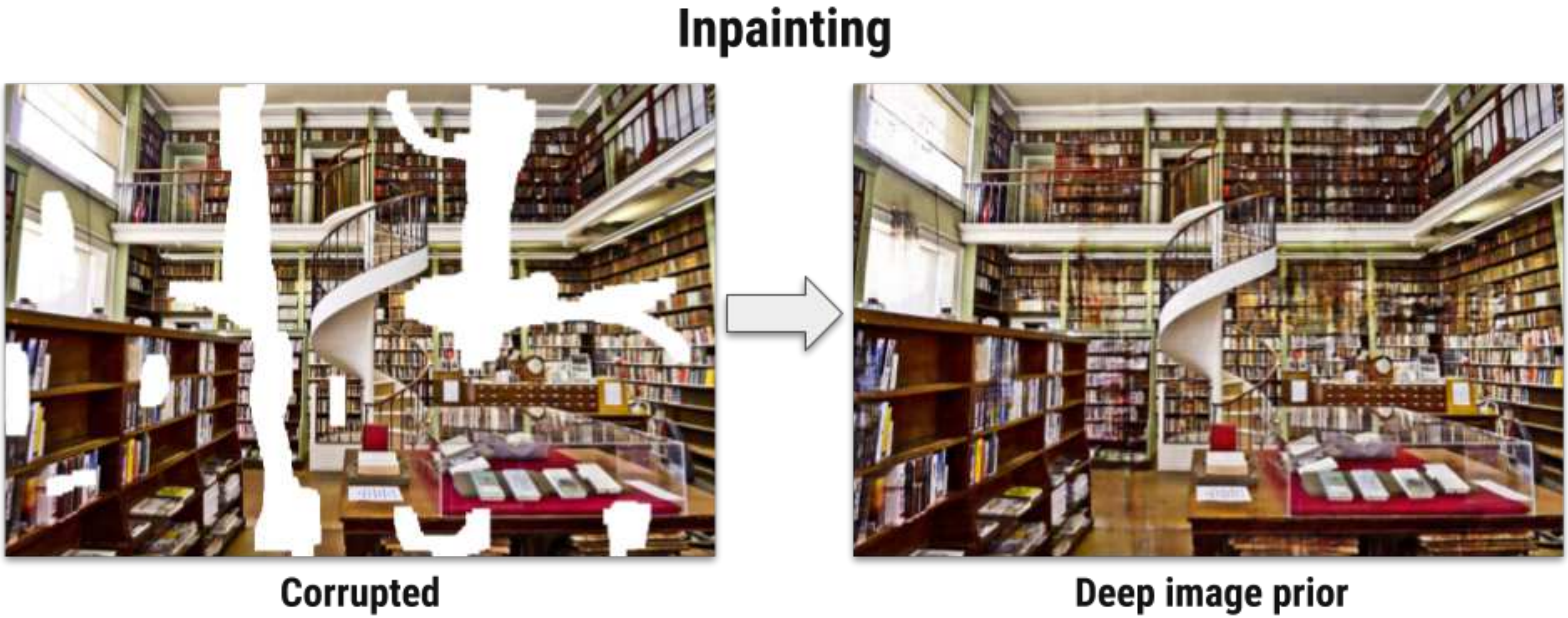


[Komiske, Metodiev, JDT, to appear]

*New insights into particle physics**
*facilitated by advances in machine learning**

Backup Slides

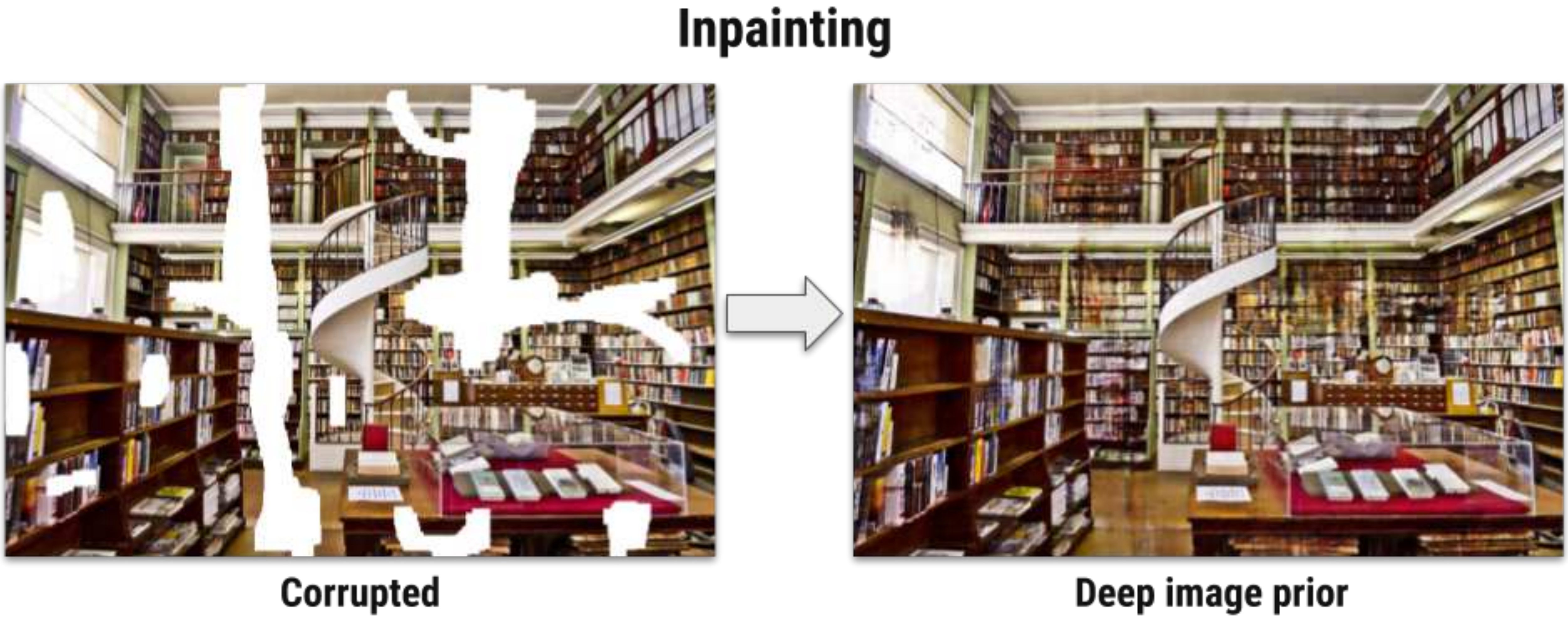
Deep Learning



increased computational power and large data sets

[Ulyanov, Vedaldi, Lempitsky, CVPR 2018]

Deep Learning (or Deep Thinking?)



Using randomly initialized neural network (!)

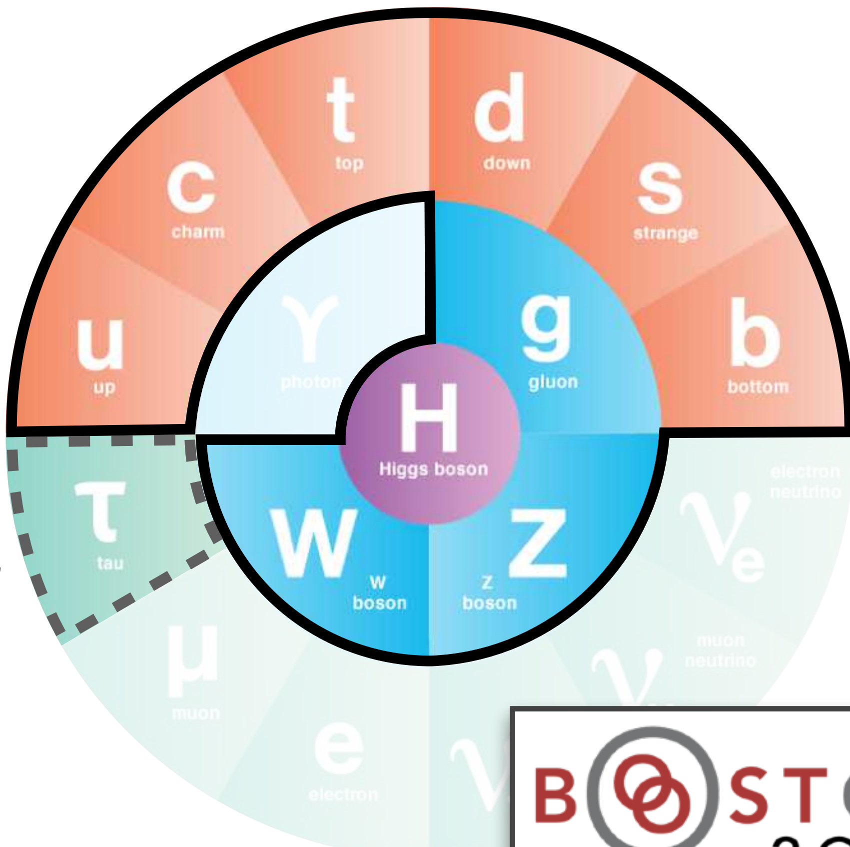
Progress made by understanding the structure of problems

(not just increased computational power and large data sets)

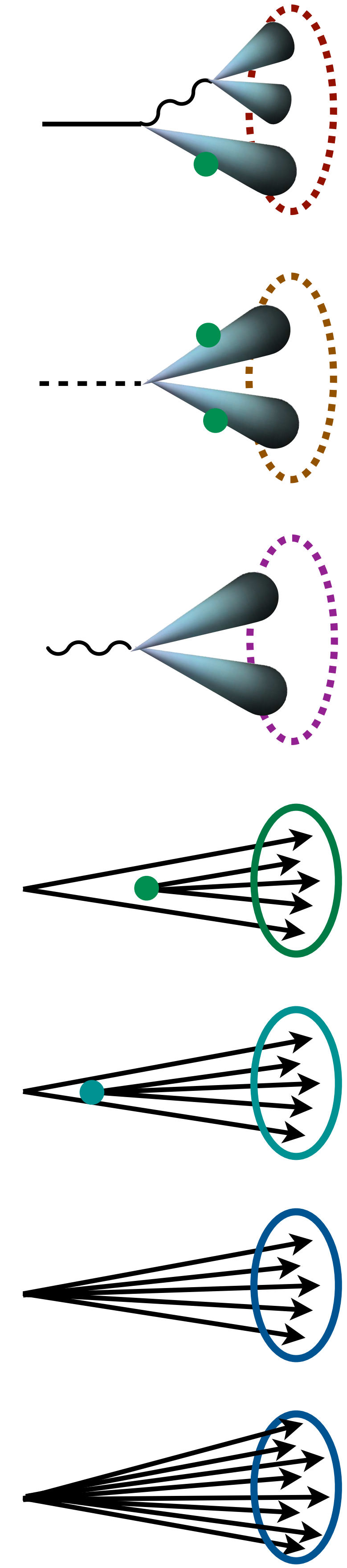
[Ulyanov, Vedaldi, Lempitsky, CVPR 2018]

Jet Classification

Key supervised learning task at LHC



micro-jet
≈ 65%

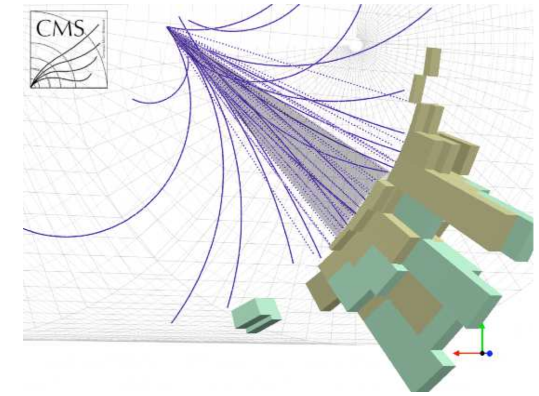


t ≈ 70%		173 GeV++
H ≈ 60%		125 GeV
W/Z ≈ 70%		80/91 GeV
b		4.2 GeV++
c		1.3 GeV++
u,d,s		100 MeV++
g		0++

++ = Mass from QCD Radiation

[see reviews in Larkoski, Moult, Nachman, arXiv 2017;
Asquith, Delitzsch, Schmidt, et al., arXiv 2018;
Marzani, Soyez, Spannowsky, LNP 2019]

Key: Jets are Point Clouds



- Particle: List of properties

$$\vec{p} = \{\underbrace{E}_{\text{Energy}}, \underbrace{p_x, p_y, p_z}_{\text{Momentum}}, \underbrace{\ldots}_{\text{Mass, charge, flavor, vertex, quality, \ldots}}\}$$

- Jet: Set of particles

$$\mathcal{J} = \{\underbrace{\vec{p}_1, \vec{p}_2, \vec{p}_3, \ldots, \vec{p}_N}_{\text{Permutation Symmetry}}\}$$

Permutation Symmetry

Quantum Mechanics:
"When you've seen one electron, you've seen them all"

Variable Length

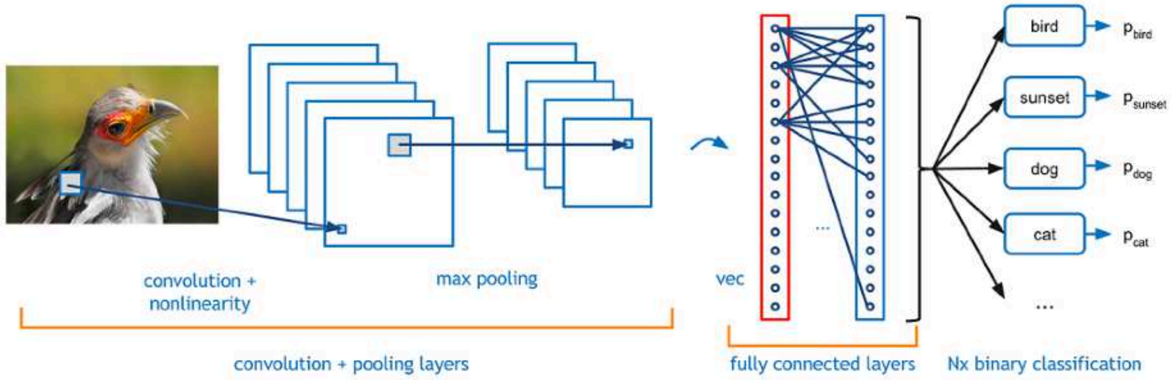
Jet Formation:
Typically 10–50 particles per jet

- Dataset: Set of jets

Off-the-Shelf Machine Learning?

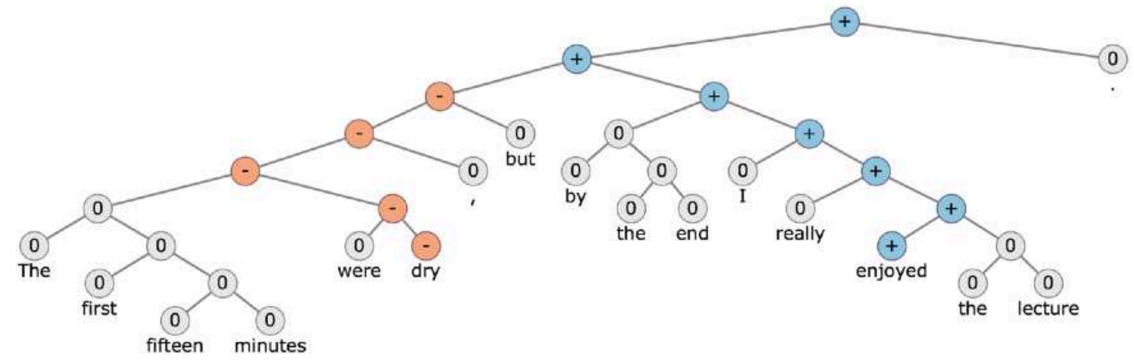
2D Images?

Appropriate for fixed-grid calorimeters,
but less ideal for tracking detectors



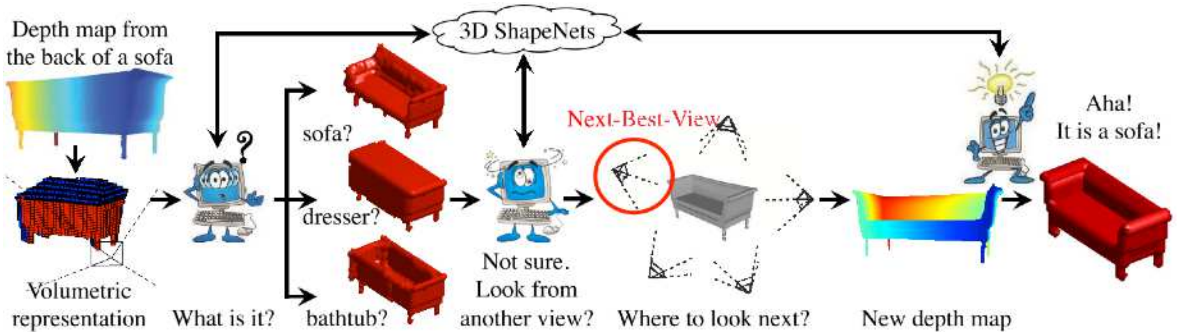
Natural Language?

Clustering can yield "semantic" structure
but inputs are fundamentally symmetric

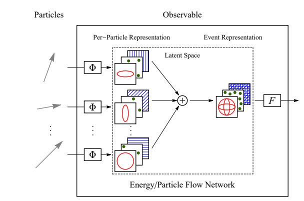


3D Objects?

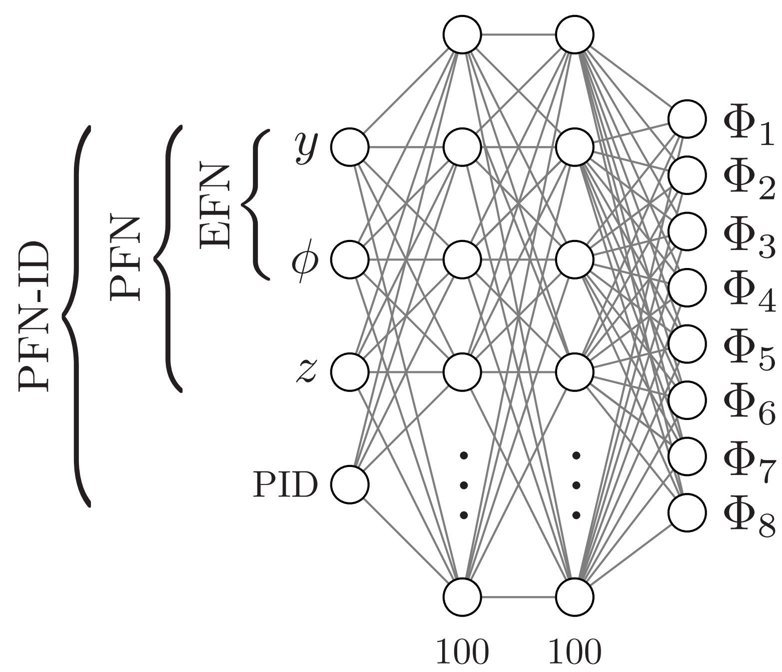
Much closer to particle physics,
but most architectures are not *"safe"*



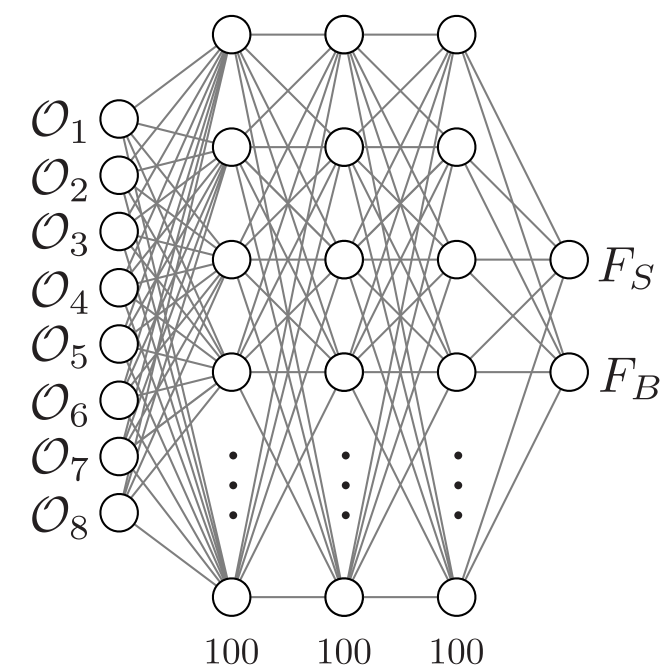
Technical Implementation



Per-Particle Network: Φ



Latent Combiner: F



Per-Jet (Latent Space):

EFN: $\mathcal{O}_a = \sum_{i \in \text{jet}} z_i \, \Phi_a(y_i, \phi_i) \qquad z_i = \frac{p_{Ti}}{\sum_j p_{Tj}}$

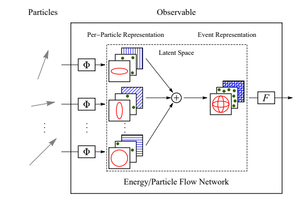
PFN: $\mathcal{O}_a = \sum_{i \in \text{jet}} \Phi_a(y_i, \phi_i, z_i, \text{PID}_i)$

Final Discriminant:

$$\text{softmax}(F_S, F_B)$$

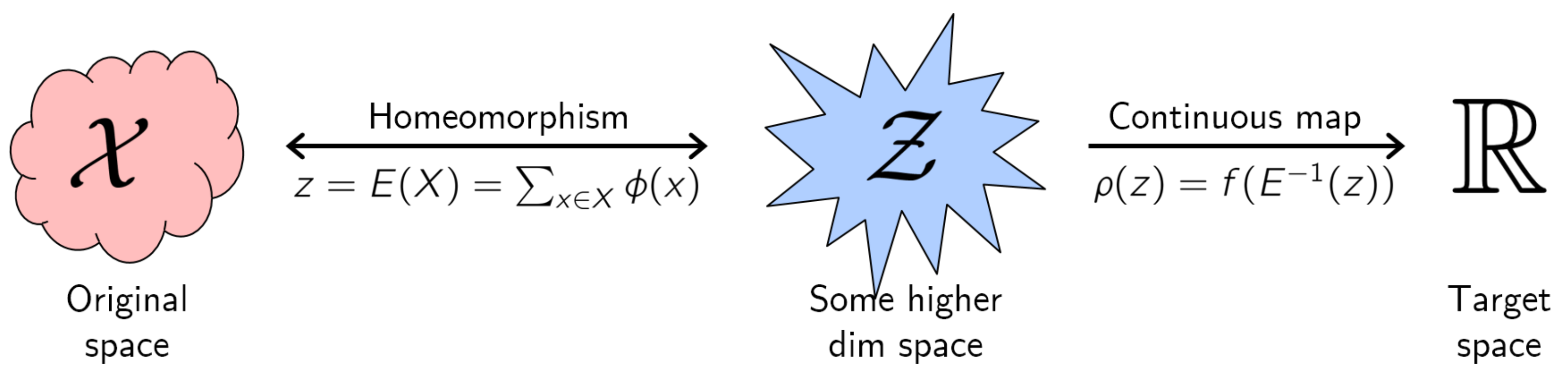
[Komiske, Metodiev, JDT, JHEP 2019]

Meanwhile in ML-Land: Deep Sets



Theorem 2 *A function $f(X)$ operating on a set X having elements from a countable universe, is a valid set function,* i.e., ***invariant*** *to the permutation of instances in X, iff it can be decomposed in the form $\rho\left(\sum_{x \in X} \phi(x)\right)$, for suitable transformations ϕ and ρ.*

(!)



Variable-Length Unordered Set of Particles

Additive Latent Space

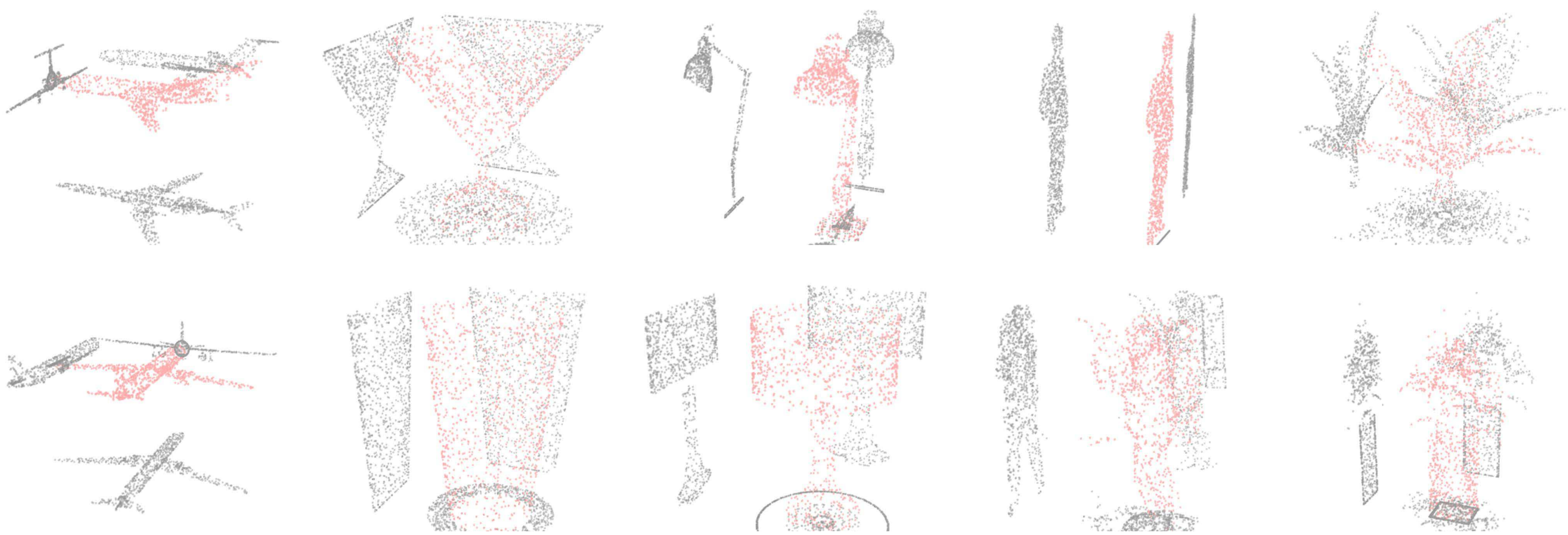
Generic Observable

[Zaheer, Kottur, Ravanbakhsh, Poczos, Salakhutdinov, Smola, 1703.06114; see also Vinyals, Bengio, Kudlur, 1511.06391; Qi, Su, Mo, Guibas, 1612.00593]

Deep Sets for…

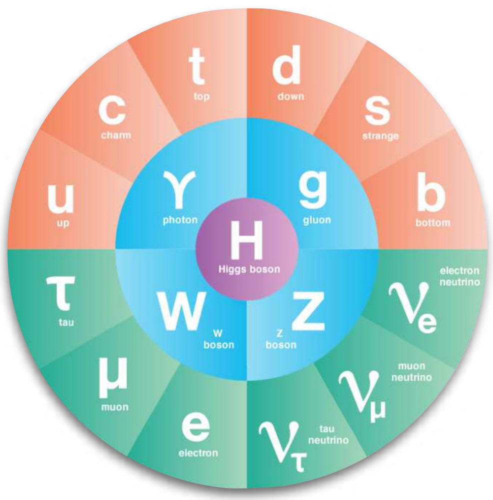
Celebrity Face Anomaly Detection

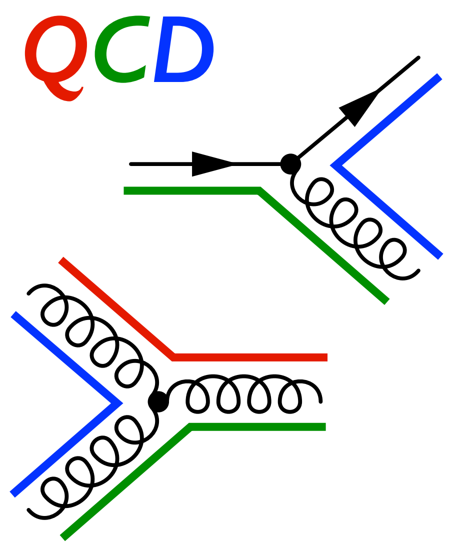
Point Cloud Classification

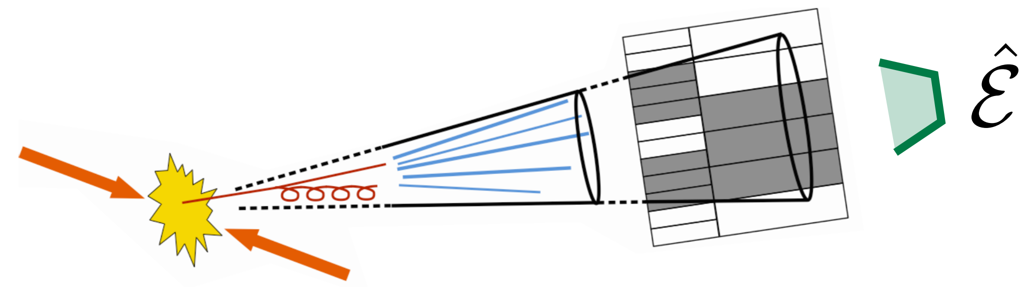


[Zaheer, Kottur, Ravanbakhsh, Poczos, Salakhutdinov, Smola, 1703.06114]

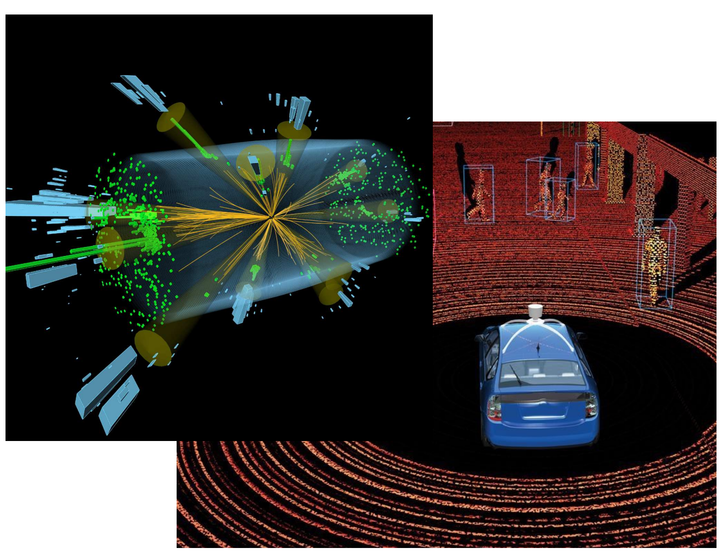
Deep Sets for Particle Jets

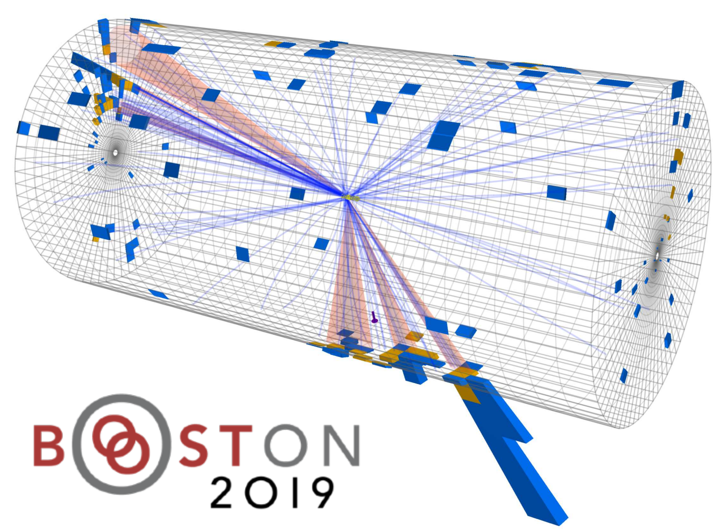


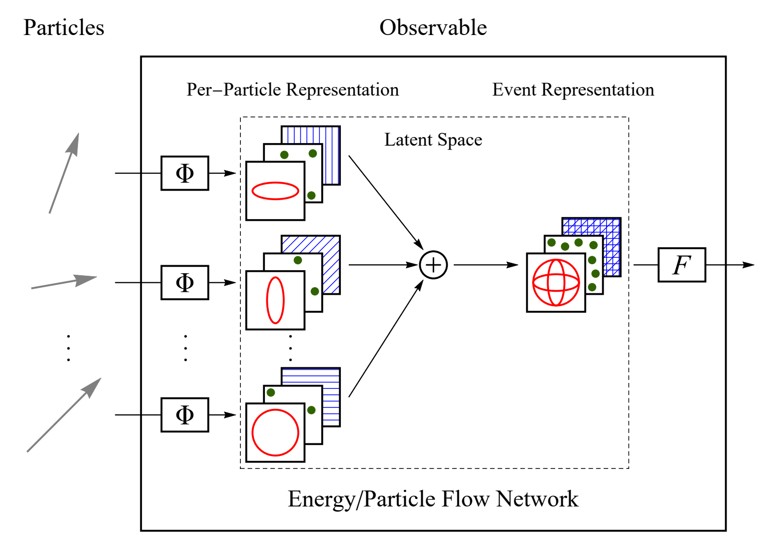




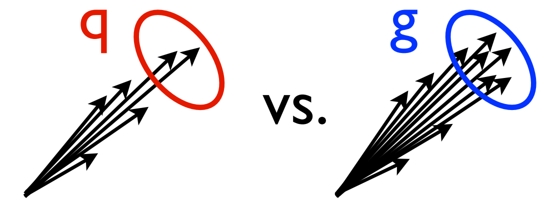
$$\mathrm{d}P_{i\to ig} \simeq \frac{2\alpha_s}{\pi} C_i \frac{\mathrm{d}\theta}{\theta} \frac{\mathrm{d}z}{z}$$

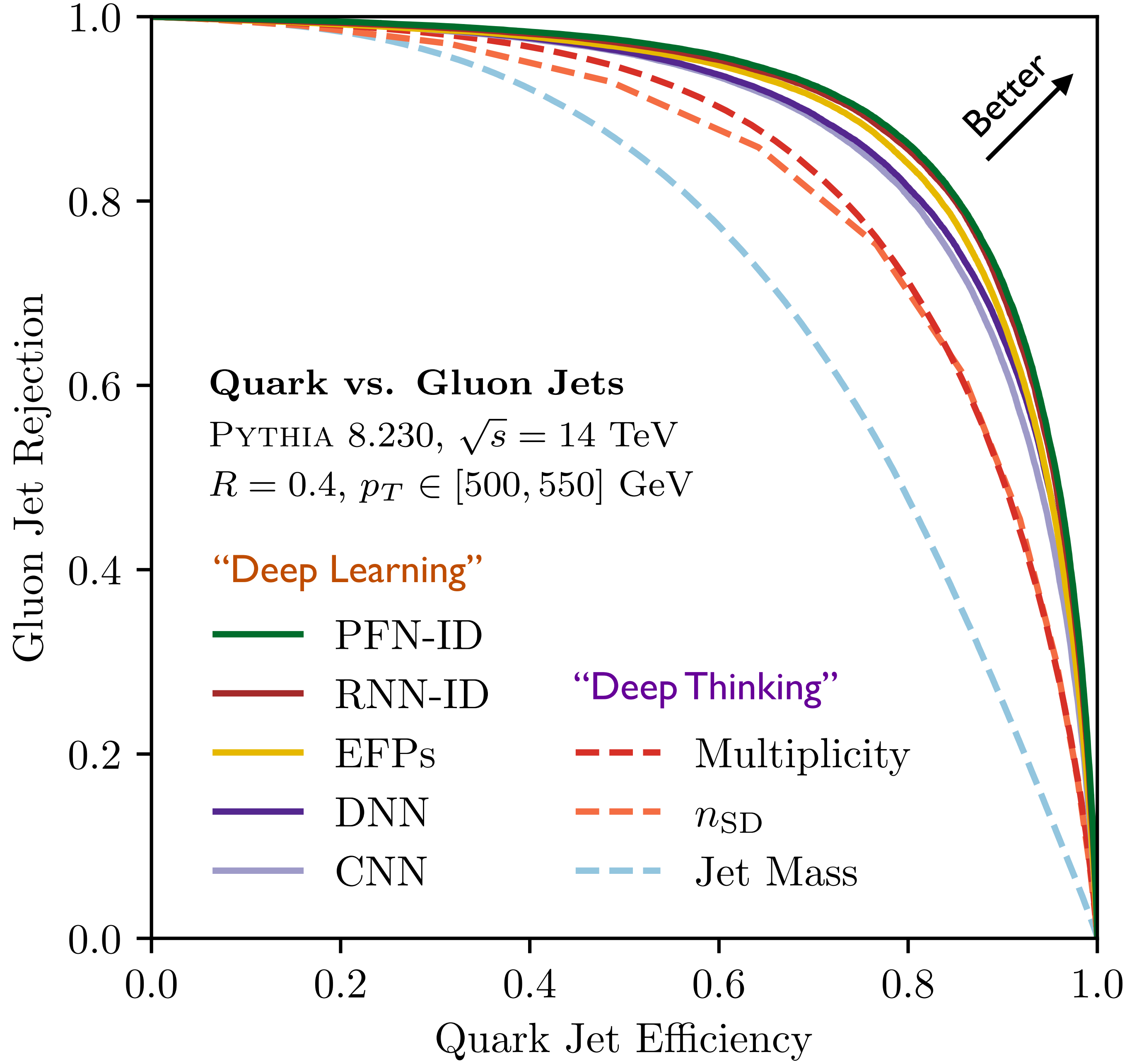






Discrimination Performance

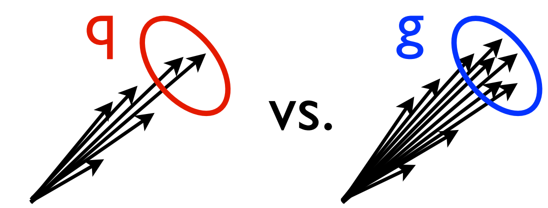


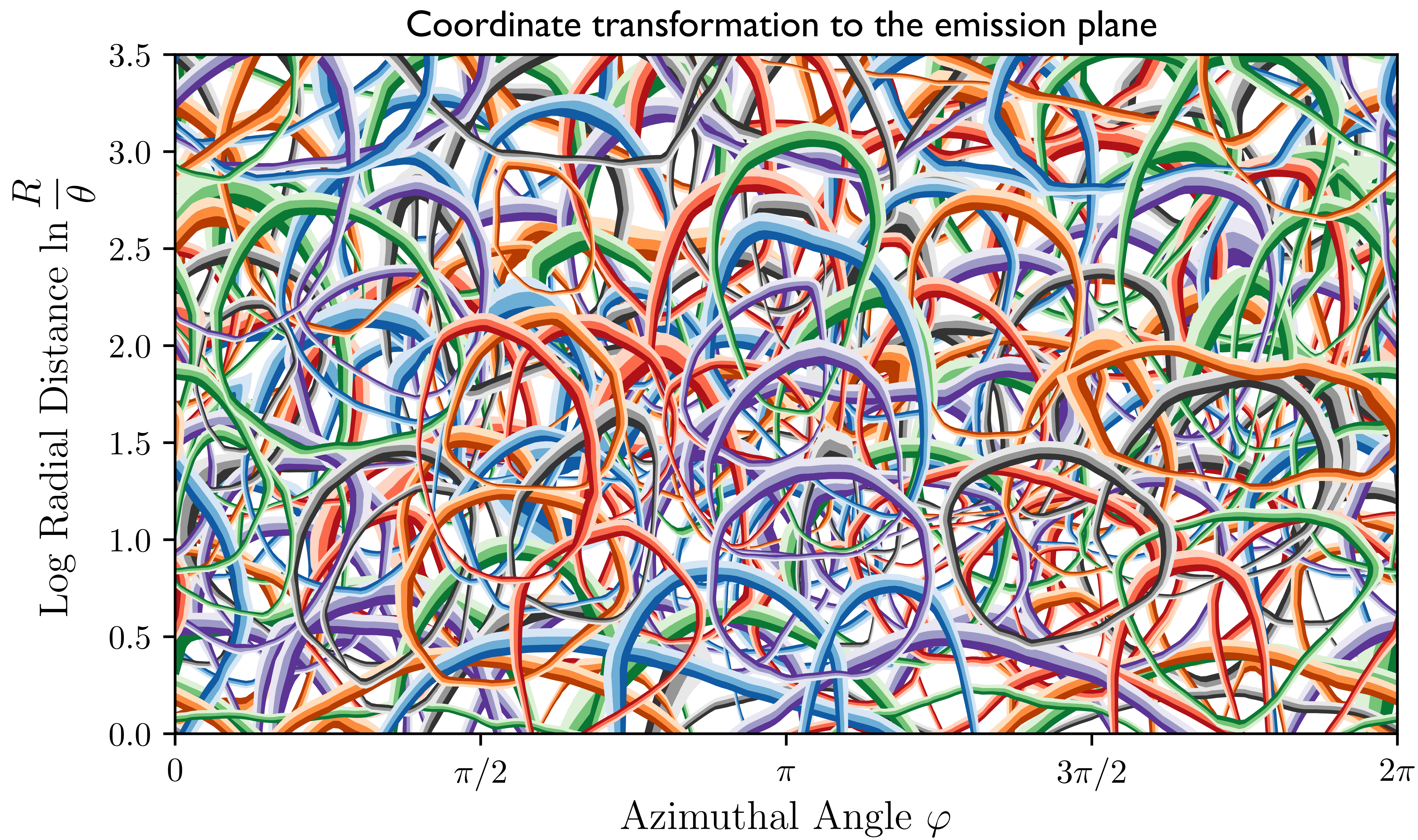


Model	AUC	$1/\varepsilon_g$ at $\varepsilon_q = 50\%$
PFN-ID	$\mathbf{0.9052} \pm 0.0007$	$\mathbf{37.4} \pm 0.7$
PFN-Ex	0.9005 ± 0.0003	34.7 ± 0.4
PFN-Ch	0.8924 ± 0.0001	31.2 ± 0.3
PFN	0.8911 ± 0.0008	30.8 ± 0.4
EFN	0.8824 ± 0.0005	28.6 ± 0.3
RNN-ID	0.9010	34.4
RNN	0.8899	30.5
EFP	0.8919	29.7
DNN	0.8849	26.4
CNN	0.8781	25.5
M	0.8401	19.0
n_{SD}	0.8297	14.2
m	0.7401	7.2

[Komiske, Metodiev, JDT, JHEP 2019]

Ready for the ICA?

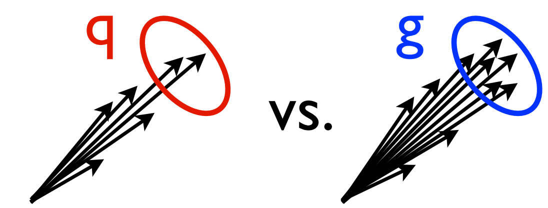




[Komiske, Metodiev, JDT, JHEP 2019; see also Dreyer, Salam, Soyez, JHEP 2018]

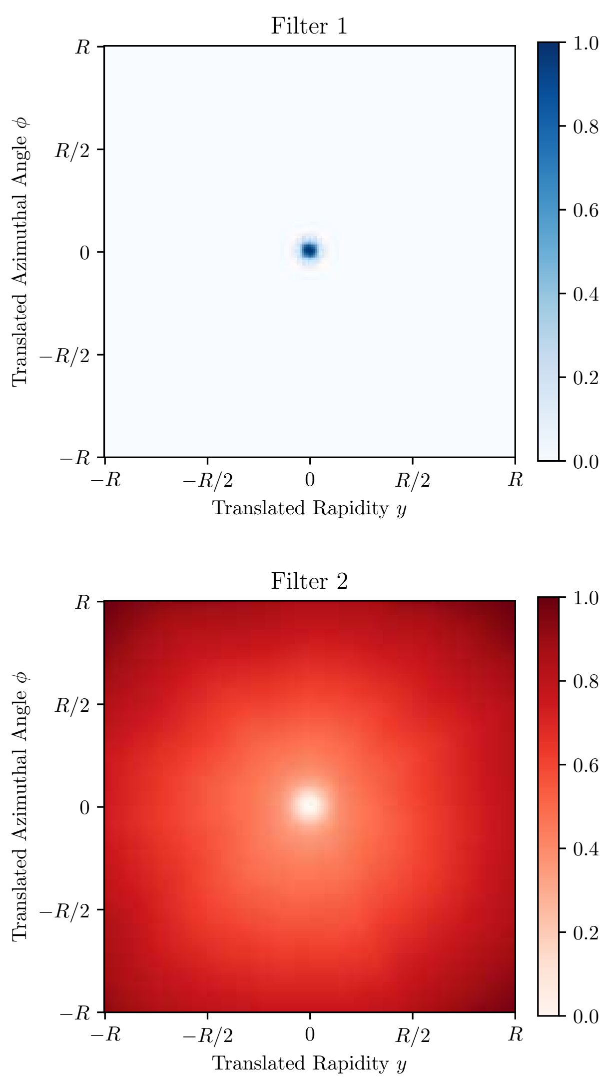
"Ok, but did you really learn something you didn't already know?"

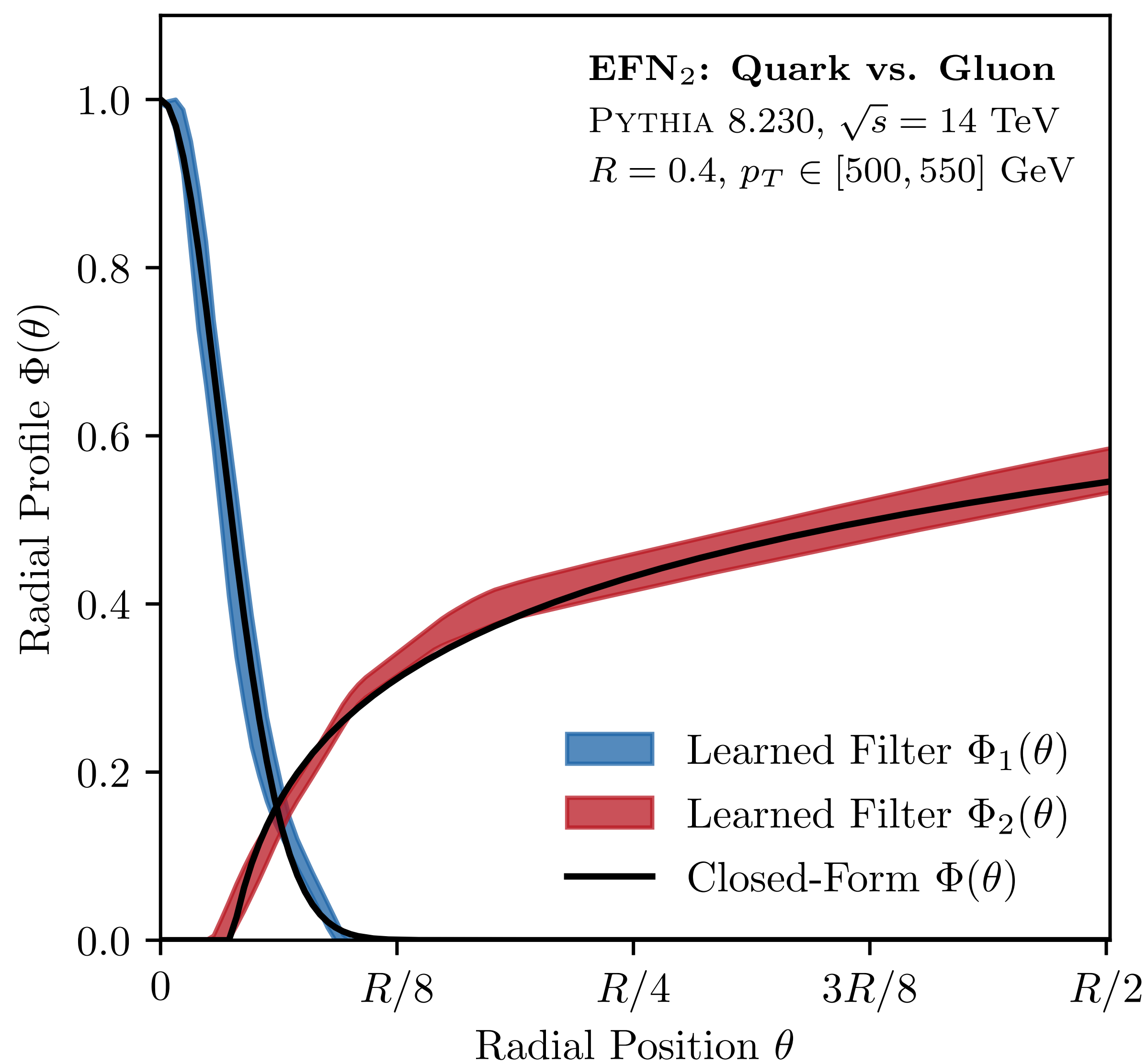
Learning from the Machine



For ℓ = 2 EFN, radial moments: $\sum_{i \in \text{jet}} z_i f(\theta_i)$

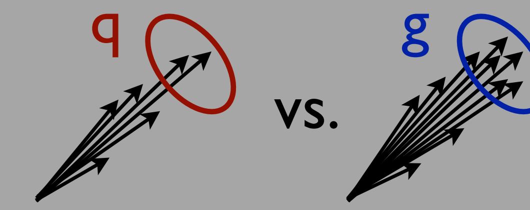
cf. Angularities: $f(\theta) = \theta^\beta$





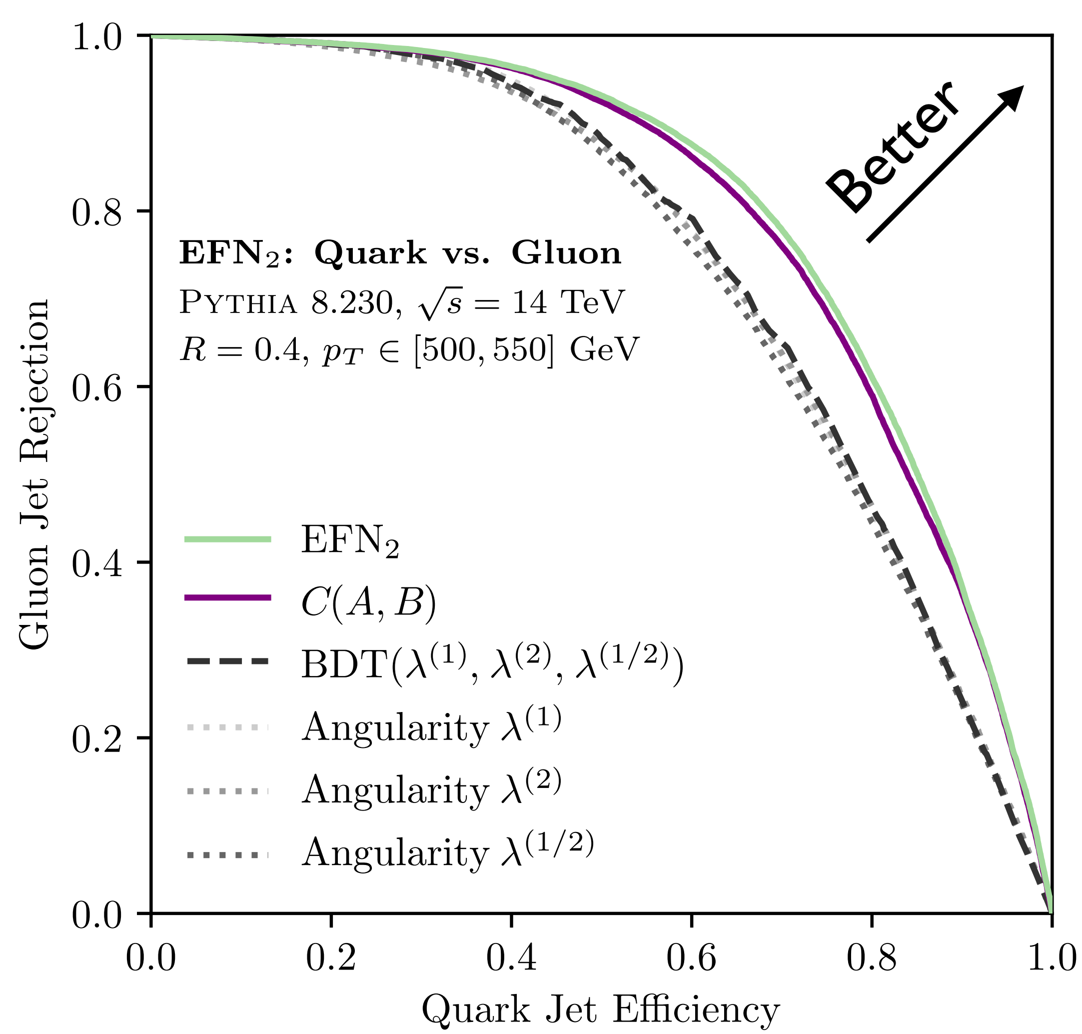
[Komiske, Metodiev, JDT, JHEP 2019;
cf. Larkoski, JDT, Waalewijn, JHEP 2014; using Berger, Kucs, Sterman, PRD 2003; Ellis, Vermilion, Walsh, Hornig, Lee, JHEP 2010]

Learning from the Machine



For ℓ = 2 EFN, radial moments: $\displaystyle\sum_{i \in \mathrm{jet}} z_i f(\theta_i)$

cf. Angularities:
$f(\theta) = \theta^\beta$



EFN outperformed a domain expert (i.e. me)

But we reverse engineered the machine (and learned something about QCD)

[Komiske, Metodiev, JDT, JHEP 2019;
cf. Larkoski, JDT, Waalewijn, JHEP 2014; using Berger, Kucs, Sterman, PRD 2003; Ellis, Vermilion, Walsh, Hornig, Lee, JHEP 2010]

The Earth Mover's Distance

Optimal Transport:

[Peleg, Werman, Rom, IEEE 1989;
Rubner, Tomasi, Guibas, ICCV 1998, ICJV 2000;
Pele, Werman, ECCV 2008; Pele Taskar, GSI 2013]

Minimum "work" (stuff x distance) to make one distribution …

The Earth Mover's Distance

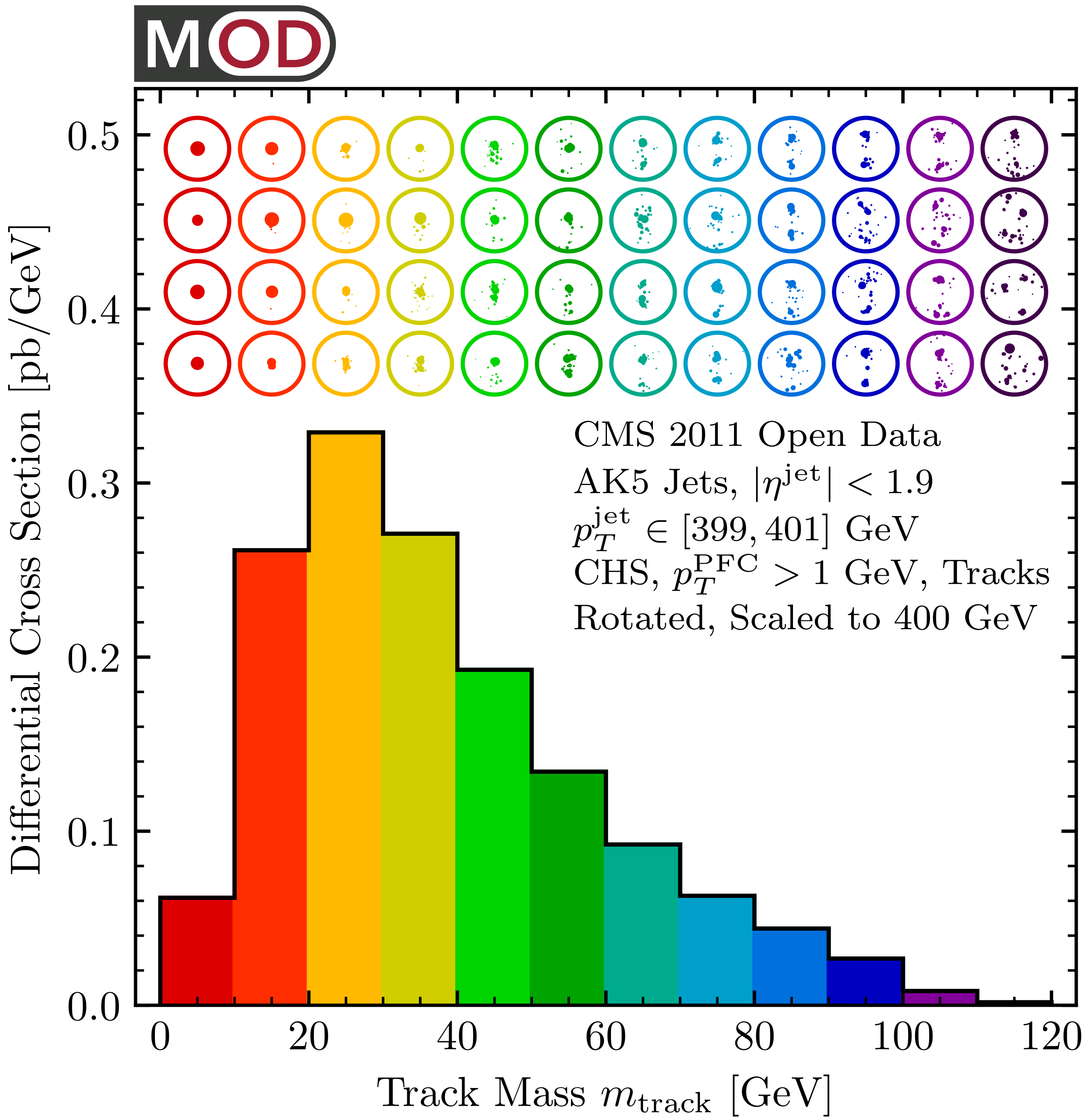
Optimal Transport: Minimum "work" (stuff x distance) to make one distribution look like another distribution

[Peleg, Werman, Rom, IEEE 1989; Rubner, Tomasi, Guibas, ICCV 1998, ICJV 2000; Pele, Werman, ECCV 2008; Pele Taskar, GSI 2013]

Equivalent to 1-Wasserstein metric; very popular in ML applications

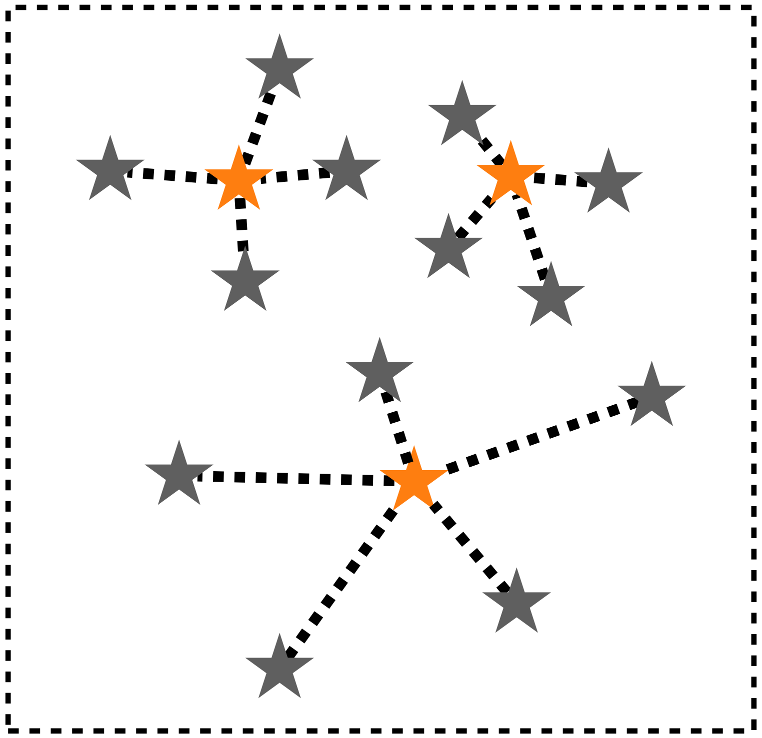
Most Representative Jets

[http://opendata.cern.ch/]



k-medoids

Per mass bin



[Komiske, Mastandrea, Metodiev, Naik, JDT, arXiv 2019]

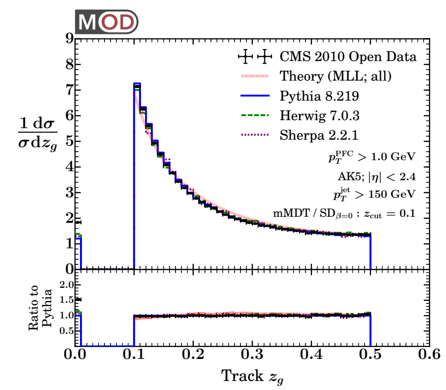
The Rise of Public Collider Data

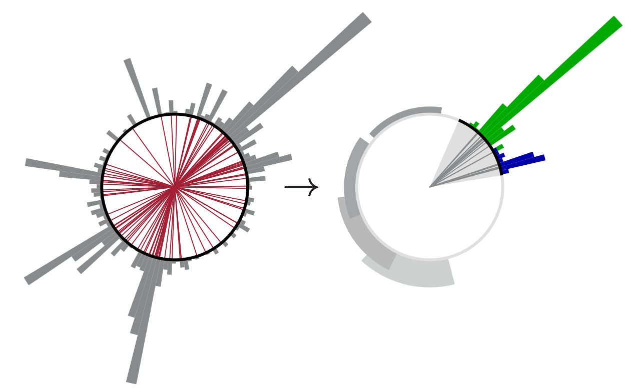
Since 2014: CMS Open Data project

[http://opendata.cern.ch/]

Standard Model & QCD

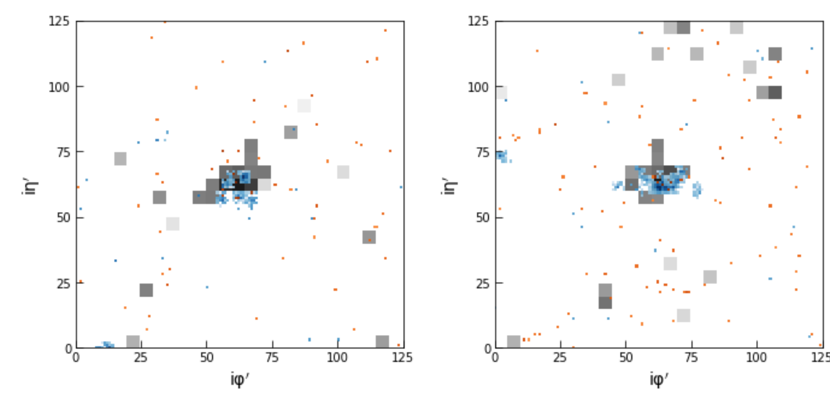
[Larkoski, Marzani, JDT, Tripathee, Xue, PRL 2017, PRD 2017;
Mehdiabadi, Fahim, arXiv 2019;
Apyan, Cuozzo, Klute, Saito, Schott, Sintayehu, arXiv 2019]





Machine Learning

[Fernndez Madrazo, Heredia Cacha, Lloret Iglesias, de Lucas, arXiv 2017;
Andrews, Paulini, Gleyzer, Poczos, arXiv 2018;
APGP + Alison, An, Bryant, Burkle, Narain, Usai, arXiv 2019;
Komiske, Mastandrea, Metodiev, Naik, JDT, arXiv 2019]



New Physics Searches

[Cesarotti, Soreq, Strassler, JDT, Xue, PRD 2019;
Lester, Schott, arXiv 2019]