Data ex Machina Machine Learning with Jets in CMS Open Data

Machine Learning for Jet Physics 2020

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CMS Open Data A new public dataset for jet studies



Unsupervised Learning A metric for collider events



Supervised Learning Training directly on collider data



CMS Open Data A new public dataset for jet studies



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Supervised Learning Training directly on collider data



About 🔻





Zenodo record

Binder demo to download and read the dataset



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When are two jets similar?

Many unsupervised methods rely on a **distance matrix.** Need a physically-sensible **metric** between jets!

These two jets "look" similar, but have different numbers of particles, flavors, and locations.



The Energy Mover's Distance

"Energy" Mover's Distance: the minimum "work" (energy x angle) to rearrange one jet (pile of energy) into another



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Six Decades of Collider Techniques



Six Decades of Collider Techniques as Optimal Transport!

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



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Metric Methods with Open Collider Data

Visualizing the Manifold

What does the space of jets look like?





Metric Methods with Open Collider Data

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]

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Visualizing the Manifold

What does the space of jets look like?





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Correlation Dimension





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Training on pure samples: Cat jets vs. Dog jets



Training on mixed samples: Cat jets vs. Dog jets



This defines an equivalent classifier to the pure case!

Training on pure samples: Quark jets vs. Gluon jets

Gluon Jets Quark Jets VS. 0 Classifier

Training on mixed samples: Quark jets vs. Gluon jets Classification central jets forward jets Without Labels (CWoLa) Quark-enriched Jets Gluon-enriched jets VS. Classifier [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 $(|\eta^{jet}| < 0.7)$: ~45% quark jetsForward Jets ($|\eta^{jet}| > 0.7$): ~65% quark jets



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

Or high-dimensional unfolding? See Patrick's Talk

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https://energyflow.network

pip install energyflow

Welcome to EnergyFlow





EnergyFlow is a Python package containing a suite of particle physics tools:

• Energy Flow Polynomials: EFPs are a collection of jet substructure observables which form a complete linear basis of IRC-safe observables. EnergyFlow provides tools to compute EFPs on





Most Representative Jets

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

Measures how "wide" the jet is.





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

The energy flow (distribution of energy) is the information that is robust to:

fragmentation, hadronization, detector effects, ...

[N.A. Sveshnikov, F.V. Tkachov, 9512370] [F.V. Tkachov, 9601308] [P.S. Cherzor, N.A. Sveshnikov, 9710349]

Energy flow \Leftrightarrow Infrared and Collinear (IRC) Safe information

The Energy Mover's Distance Review: The Earth Mover's Distance

Earth Mover's Distance: the minimum "work" (stuff x distance) to rearrange one pile of dirt into another [Peleg, Werman, Rom]

[Rubner, Tomasi, Guibas]

Metric on the space of (normalized) distributions: symmetric, non-negative, triangle inequality

Distributions are close in EMD \Leftrightarrow their expectation values are close.

Also known as the 1-Wasserstein metric.

The Energy Mover's Distance

From Earth to Energy

Energy Mover's Distance: the minimum "work" (energy x angle) to rearrange one event (pile of energy) into another [Komiske, EMM, Thaler, 1902.02346]

The Energy Mover's Distance

From Earth to Energy

Energy Mover's Distance: the minimum "work" (energy x angle) to rearrange one event (pile of energy) into another [Komiske, EMM, Thaler, 1902.02346]

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

EMD has dimensions of energy

True metric as long as $R \ge \frac{1}{2}\theta_{\max}$ $R \ge$ the jet radius, for conical jets

Solvable via Optimal Transport problem. ~1ms to compute EMD for two jets with 100 particles.

From Earth to Energy

Energy Mover's Distance: the minimum "work" (energy x angle) to rearrange one event (pile of energy) into another [Komiske, EMM, Thaler, 1902.02346]

Energy Moving and IRC Safety

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

Old Observables in a New Language

Geometry in the space of events

Thrust is the EMD between the event and two back-to-back particles.

$$t(\mathcal{E}) = E - \max_{\hat{n}} \sum_{i} |\vec{p}_{i} \cdot \hat{n}| \longrightarrow t(\mathcal{E}) = \min_{\substack{|\mathcal{E}'|=2 \\ \text{with } \theta_{ij} = \hat{n}_{i} \cdot \hat{n}_{j}, \ \hat{n} = \vec{p}/E}} EMD(\mathcal{E}, \mathcal{E}')$$

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Data ex Machina: ML with Jets in CMS Open Data

Quantifying Pileup and Detector Effects with EMD

Gen./Sim. EMD universally quantifies pileup and detector effects.

See extra slides for histograms. Can also quantify hadronization effects this way.

Data ex Machina: ML with Jets in CMS Open Data

Exploring the Space of Jets: Visualizing the Manifold

Visualize the space of events with t-Distributed Stochastic Neighbor Embedding (t-SNE).

[L. van der Maaten, G. Hinton]

Finds an embedding into a low-dimensional manifold that respects distances.

What does the space of jets look like?

Quantity (and calculate!) dimension of the space of jets. See ext

Exploring the Space of Jets: Correlation Dimension

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PHYSICAL REVIEW LETTERS

31 JANUARY 1983

Characterization of Strange Attractors

Peter Grassberger^(a) and Itamar Procaccia Chemical Physics Department, Weizmann Institute of Science, Rehovot 76100, Israel (Received 7 September 1982)

A new measure of strange attractors is introduced which offers a practical algorithm to determine their character from the time series of a single observable. The relation of this new measure to fractal dimension and information-theoretic entropy is discussed.

Intuition:

 $N_{\text{neighboring}}(r) \propto r^{\dim}$ points

dim≃l

dim≃2

(eventually 0)

Correlation dimension:

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Exploring the Space of Jets: Correlation Dimension

low energies.

Jets are "more than fractal"

CMS Open Data

Many exciting physics applications with the CMS Open Data already.

Quantifying Pileup and Detector Effects with EMD

Gen./Sim. EMD universally quantifies pileup mitigation and detector effects.

Jet Substructure Observables

Study jet substructure at truth and detector level.

Similar to: [Larkoski, Marzani, Thaler, Tripathee, Xue, 1704.05066]

Exploring the Space of Jets: Correlation Dimension

Jet Kinematic Distributions

Exploring the Space of Events: Jet Classification

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Exploring the Space of Events

Use EMD as a measure of event similarity

Unsupervised clustering algorithms can be used to cluster events

Jets are clusters of particles ???? are clusters of jets

VP Tree: O(log(N)) neighbor query time

Much more to explore.

Vantage Point (VP) Tree

Exploring the Space of Events: W jets

Exploring the Space of Jets: Correlation Dimension

 $\dim_{q/g}(Q) = Q \frac{\partial}{\partial Q} \ln \sum_{i=1}^{N} \sum_{j=1}^{N} \Theta[\text{EMD}(\varepsilon_i, \varepsilon_j) < Q]$ $= Q \frac{\partial}{\partial Q} \ln \Pr \left[\text{EMD} < Q \right]$ $= Q \frac{\partial}{\partial Q} \ln \Pr\left[\lambda^{(\beta=1)} < Q; C_{q/g} \to 2 C_{q/g}\right]$ $= Q \frac{\partial}{\partial Q} \ln \exp\left(-\frac{4\alpha_S C_{q/g}}{\pi} \ln^2 \frac{Q}{p_T/2}\right)$ $= -\frac{8\alpha_s C_{q/g}}{\pi} \ln \frac{Q}{p_T/2} \qquad \qquad C_q = C_F = \frac{4}{3}$ I-loop running of $\alpha_s \qquad \qquad C_g = C_A = 3$ + 1-loop running of α_s

Sketch of leading log (one emission) calculation:

