

Understanding QCD at the Large Hadron Collider, Part 1

Andrew Larkoski
Reed College

New Physics from Precision at High Energies, KITP, April 15 2021

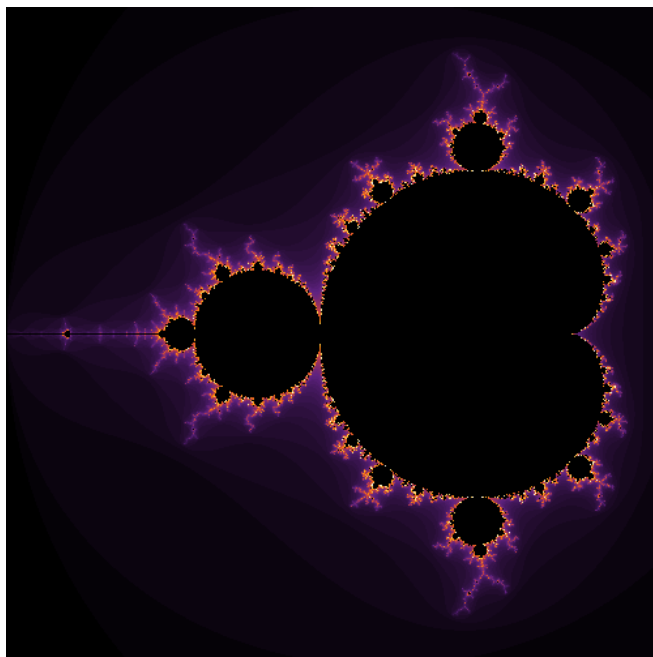
Human Learning from Thinking Like a Machine

Andrew Larkoski
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New Physics from Precision at High Energies, KITP, April 15 2021

Losing the Particle Physics Forest for the ML/AI/CS Trees

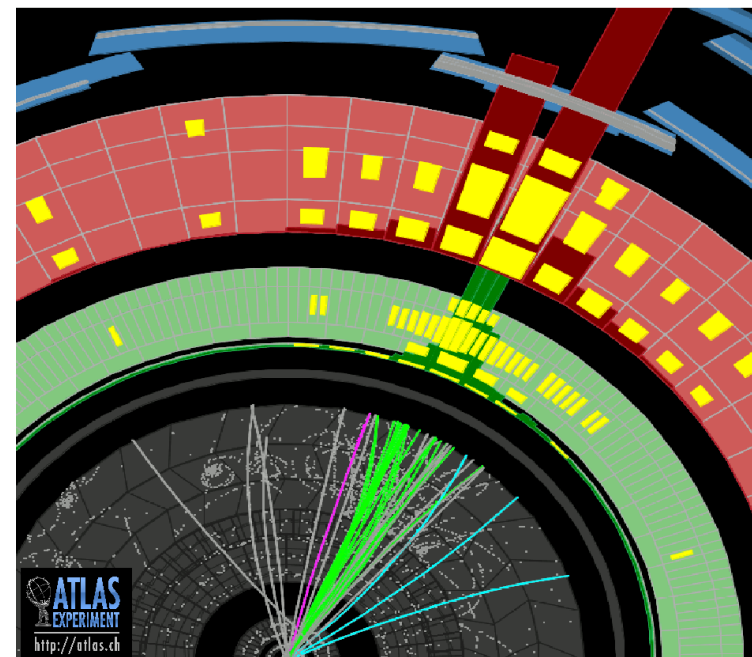
Information content of a particle physics event or jet is small



Kolmogorov complexity of Mandelbrot set is small
(easy to write a short computer program)

This image: 100,000s of pixels

Program to generate it: 2 lines of code



arXiv:1112.6426

One jet with 30ish particles; ~3000 total bits

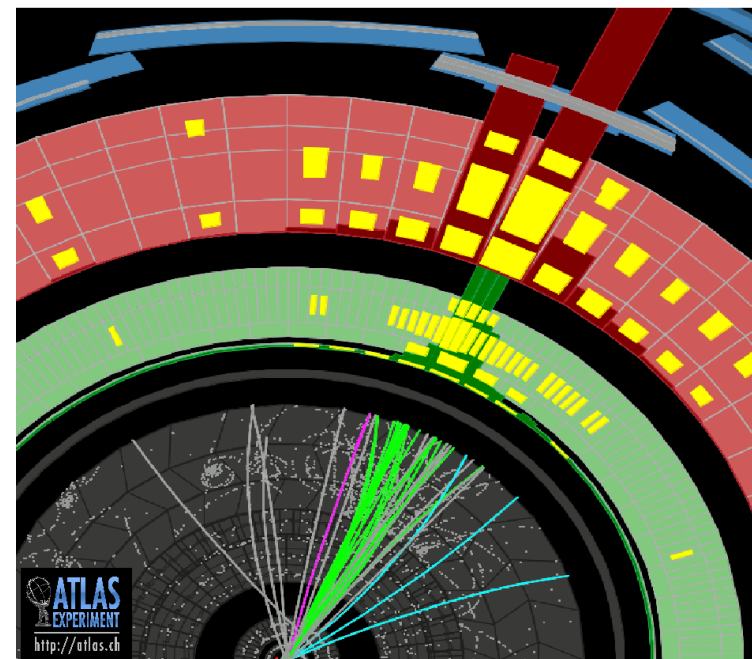
LHC has recorded > 10 billion events

Pythia + MadGraph code is about 50 MBytes

Information in physics <<<<< information of data

Losing the Particle Physics Forest for the ML/AI/CS Trees

We know the rules of particle physics and the space in which the data lives



arXiv:1112.6426

What is the space of pixels in an image of Brad Pitt?

What theory governs his chiseled brow?

Whole subfields of CS are devoted to organizing data with no known structure

Fundamental theory: the QCD Lagrangian

Particle production governed by recursive equations

Resulting particles live on relativistic phase space

Recall: A Lesson for Introductory Physics

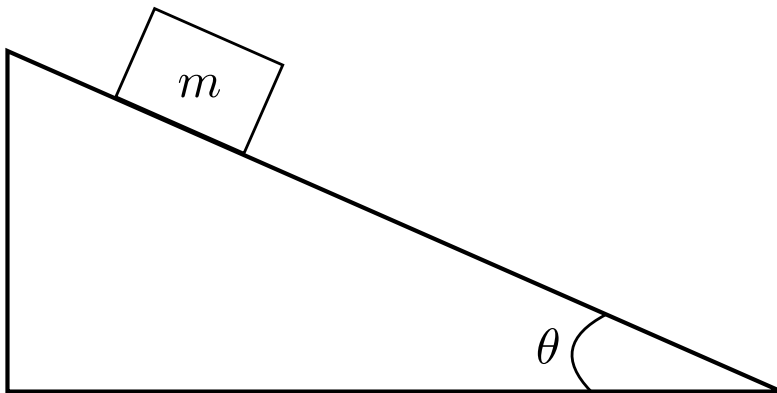
Students in introductory physics haven't honed their physical intuition

To make something habit, you have to consciously do the action 1000s of times

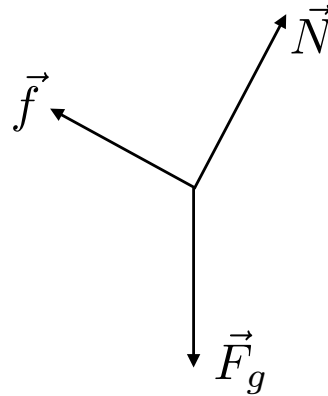
If you learn a new physics concept and are asked to solve a problem you must consciously ask:

What is the dumbest next thing that I could do?

Problem:



1st dumb thing: FBD



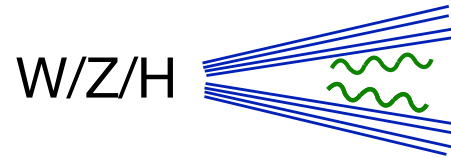
2nd dumb thing: Newton #2

$$\vec{F}_g + \vec{N} + \vec{f} = m\vec{a}$$

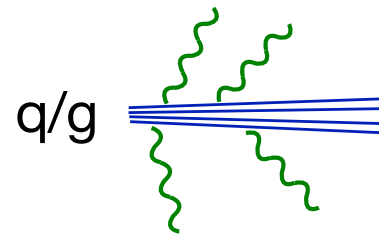
If the dumbest thing works, then it isn't so dumb, and you can completely understand everything

Example 1: Optimal Observables for Color-Singlet Identification

Problem:



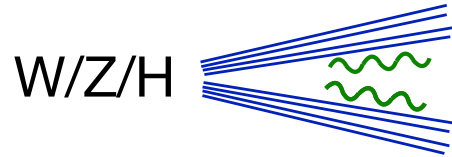
vs.



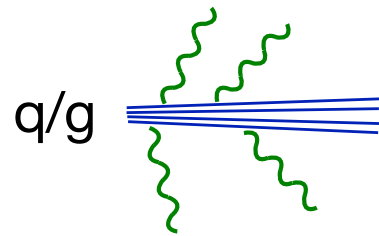
Already assume that there is
selected hard two-prong structure

Example 1: Optimal Observables for Color-Singlet Identification

Problem:

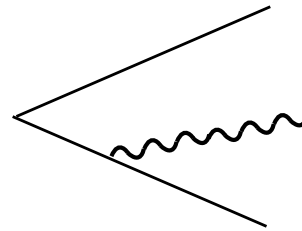


vs.



1st dumb thing:

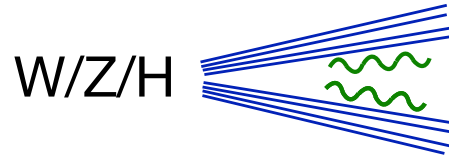
Jet has 3 particles,
minimal for color correlations



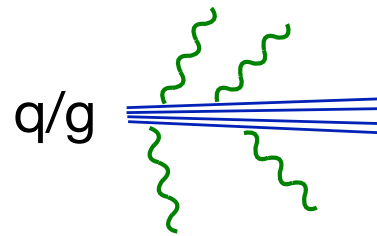
Work in limit where third particle is
much softer than other two

Example 1: Optimal Observables for Color-Singlet Identification

Problem:

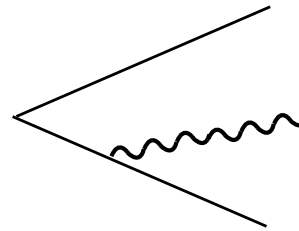


vs.



1st dumb thing:

Jet has 3 particles,
minimal for color correlations



2nd dumb thing:

Neyman-Pearson:

Likelihood ratio is optimal

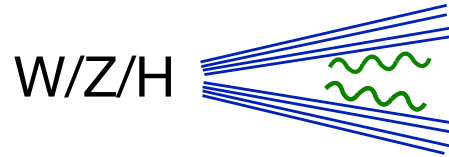
Neyman, Pearson 1933

$$\mathcal{O} = \frac{|\mathcal{M}_{\text{QCD}}|^2}{|\mathcal{M}_{\text{singlet}}|^2}$$

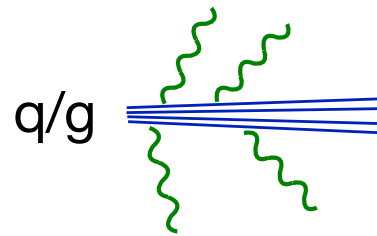
Best discriminant is some function
of the location of the soft particle

Example 1: Optimal Observables for Color-Singlet Identification

Problem:



vs.



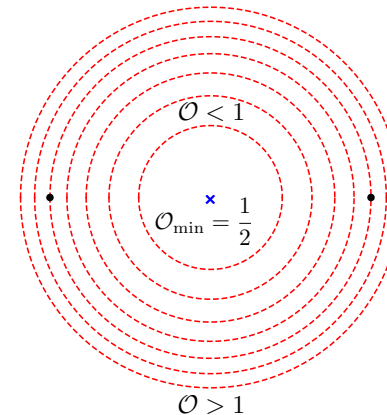
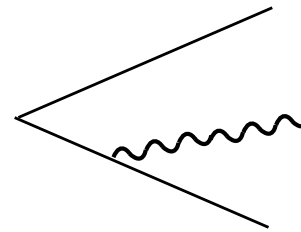
Consequences:

Observables “designed” to do this are suboptimal

See also [arXiv:2010.11998](https://arxiv.org/abs/2010.11998)

1st dumb thing:

Jet has 3 particles,
minimal for color correlations



Contours of constant optimal observable

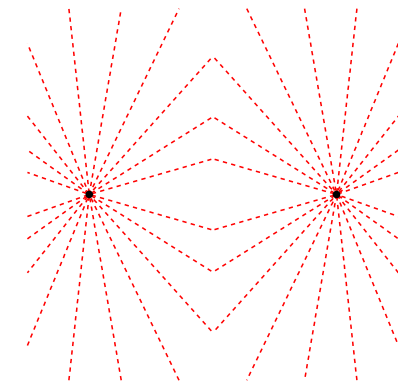
“jet color ring”

2nd dumb thing:

Neyman-Pearson:
Likelihood ratio is optimal

[Neyman, Pearson 1933](#)

$$\mathcal{O} = \frac{|\mathcal{M}_{\text{QCD}}|^2}{|\mathcal{M}_{\text{singlet}}|^2}$$



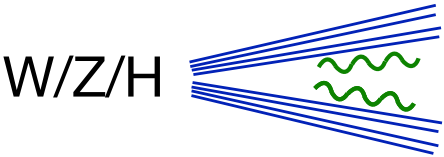
Contours of constant pull angle

[arXiv:1001.5027](https://arxiv.org/abs/1001.5027)

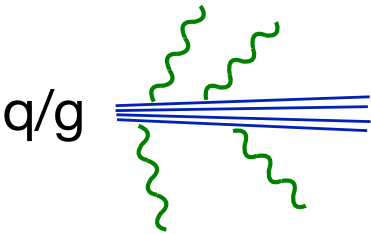
[arXiv:2006.10480](https://arxiv.org/abs/2006.10480)

Example 1: Optimal Observables for Color-Singlet Identification

Problem:



vs.

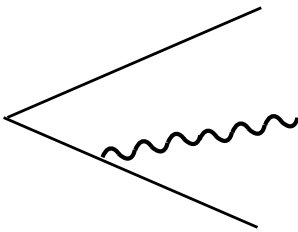


Consequences:

Discrimination works in simulation

1st dumb thing:

Jet has 3 particles,
minimal for color correlations



2nd dumb thing:

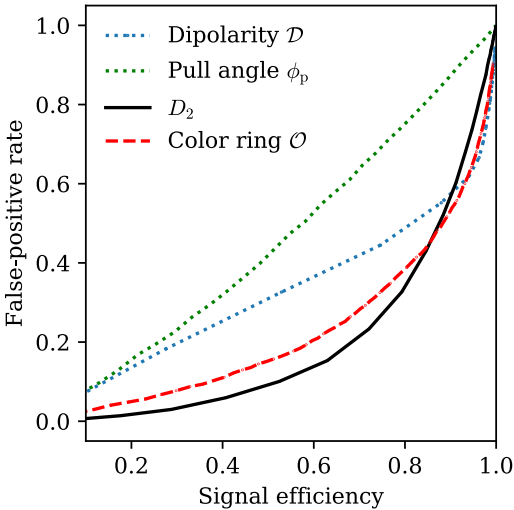
Neyman-Pearson:
Likelihood ratio is optimal

Neyman, Pearson 1933

$$\mathcal{O} = \frac{|\mathcal{M}_{\text{QCD}}|^2}{|\mathcal{M}_{\text{singlet}}|^2}$$

D_2 still apparently has some
interesting color information

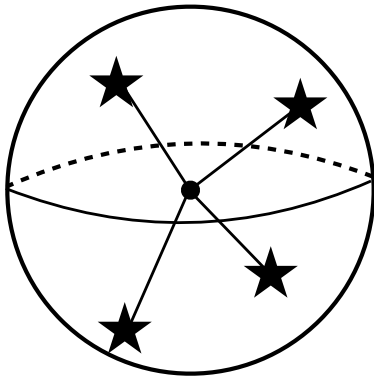
arXiv:1409.6298



Example 2: The Topology of Phase Space

Problem:

What is the manifold on which particles in collision event live?



For simplicity, let's take all particles as massless

Example 2: The Topology of Phase Space

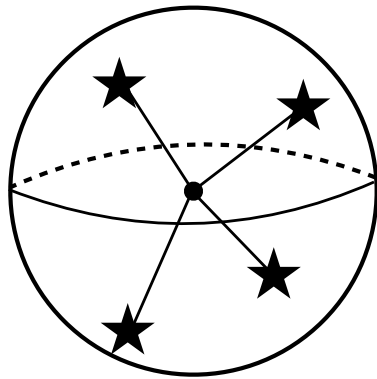
Problem:

1st dumb thing:

What is the manifold on which particles in collision event live?

Answer: Relativistic N-body phase space

Dirac 1927



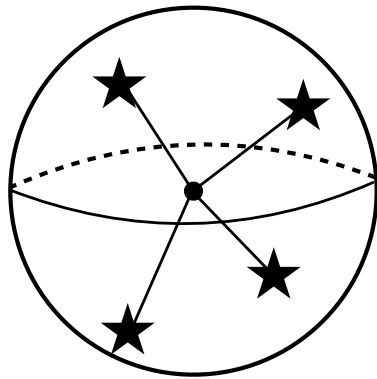
$$d\Pi_N = \prod_{i=1}^N [d^4 p_i]_+ \delta^{(4)} \left(Q - \sum_{i=1}^N p_i \right)$$

All particles are on-shell, have positive energy, and total momentum is conserved

Example 2: The Topology of Phase Space

Problem:

What is the manifold on which particles in collision event live?



1st dumb thing:

Answer: Relativistic N-body phase space

Dirac 1927

$$d\Pi_N = \prod_{i=1}^N [d^4 p_i]_+ \delta^{(4)} \left(Q - \sum_{i=1}^N p_i \right)$$

2nd dumb thing:

Simplify and rewrite in a form that makes geometry manifest

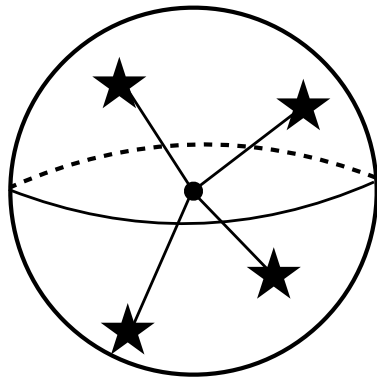
$$\Pi_N \simeq \Delta_{N-1} \times S^{2N-3}$$

Isomorphic to the product of the $N-1$ simplex and the $2N-3$ sphere

Example 2: The Topology of Phase Space

Problem:

What is the manifold on which particles in collision event live?



Consequences:

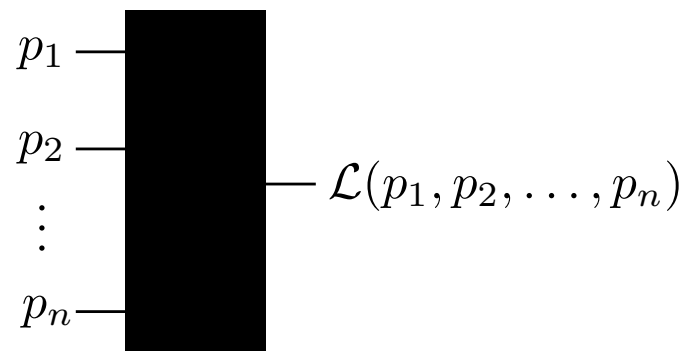
Phase space is **not** Euclidean space

1st dumb thing:

Answer: Relativistic N-body phase space

Dirac 1927

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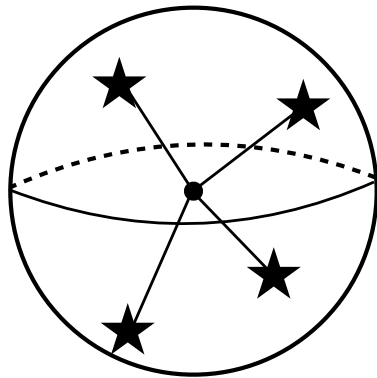
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ML techniques that assume flat space might fail on a curved manifold

Example 2: The Topology of Phase Space

Problem:

What is the manifold on which particles in collision event live?



Consequences:

Problems with autoencoders on non-trivial manifolds

1st dumb thing:

Answer: Relativistic N-body phase space

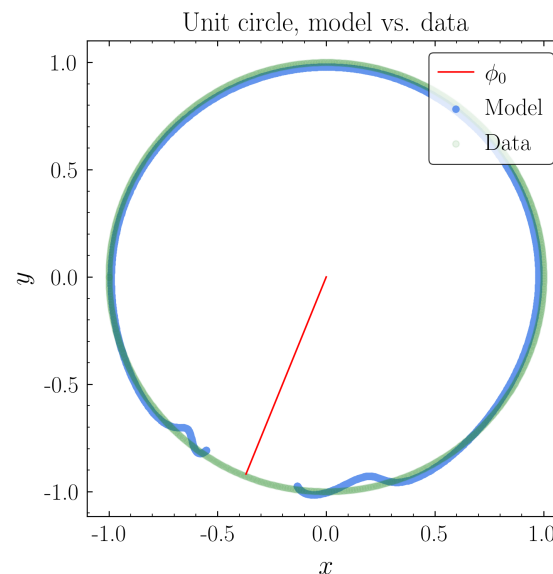
Dirac 1927

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Simplify and rewrite in a form that makes geometry manifest

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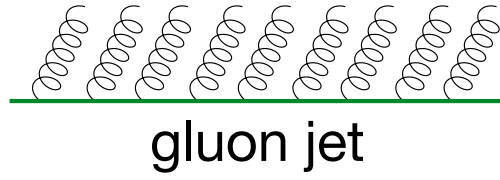
Textbook example of spontaneous symmetry breaking

Autoencoder “tears” manifold at random point

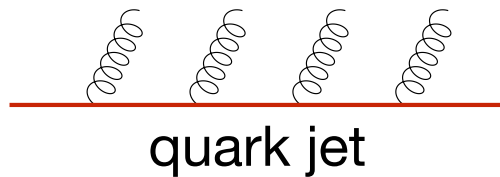
arXiv:2102.08380

Example 3: The Likelihood for Quark vs. Gluon Discrimination

Problem:



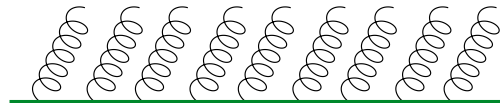
vs.



Just assume that the only
difference is the total color

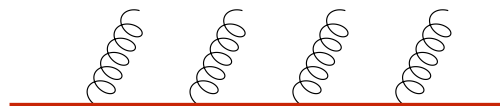
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gluon jet

vs.



quark jet

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Most naive results from stats/ML

Universal Approx.

Theorem

Cybenko 1989, etc

$$\mathcal{L}(\{p_i\}) = \mathcal{L}(\{x_i\})$$

Neyman-Pearson

Lemma

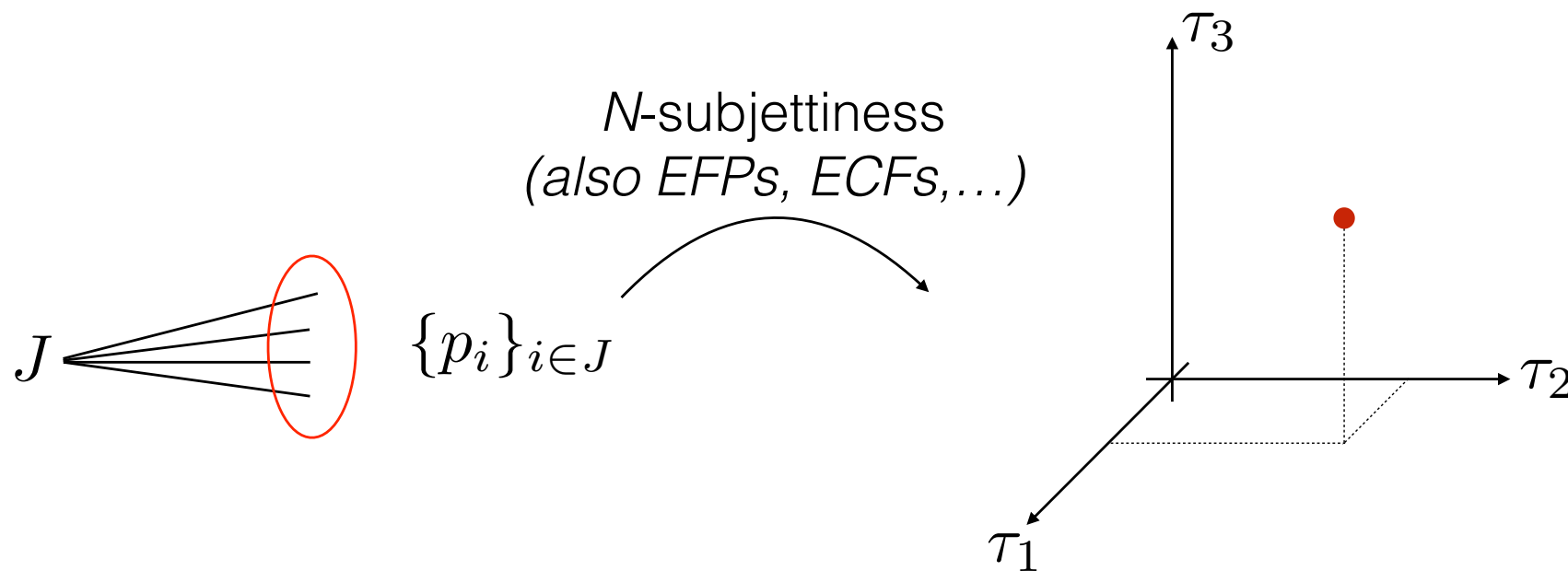
Neyman, Pearson 1933

$$\mathcal{L}(\{x_i\}) = \frac{p_g(\{x_i\})}{p_q(\{x_i\})}$$

Choose a basis of IRC safe observables
to express particle momenta

Example 3: The Likelihood for Quark vs. Gluon Discrimination

N -subjettiness and related observables accomplish this



arXiv:1704.08249

history:

arXiv:1004.2489, 1011.2268, 1108.2701

Brandt, Dahmen 1979

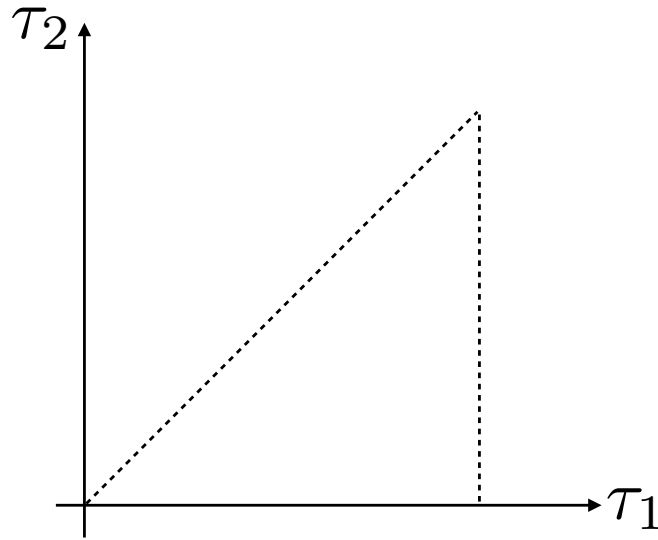
Wu, Zobernig 1979

Nachtmann, Reiter 1982

$$\tau_N^{(\beta)} = \frac{1}{p_{TJ}} \sum_{i \in J} p_{Ti} \min \left\{ R_{1i}^\beta, R_{2i}^\beta, \dots, R_{Ni}^\beta \right\}$$

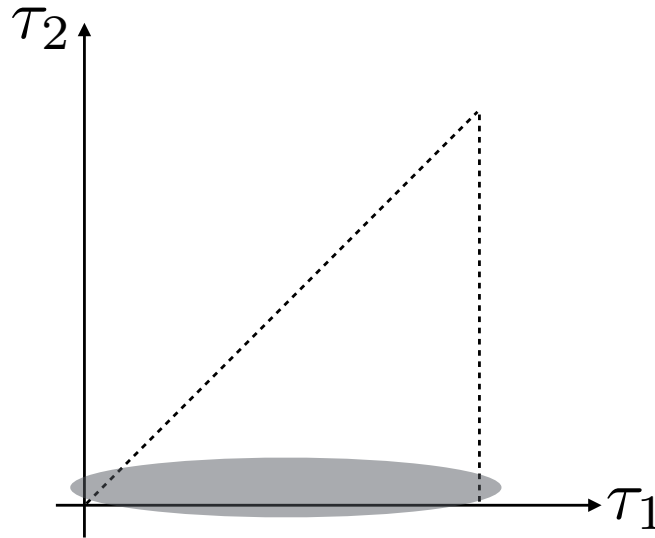
Example 3: The Likelihood for Quark vs. Gluon Discrimination

For visualization simplicity, just consider (τ_1, τ_2)



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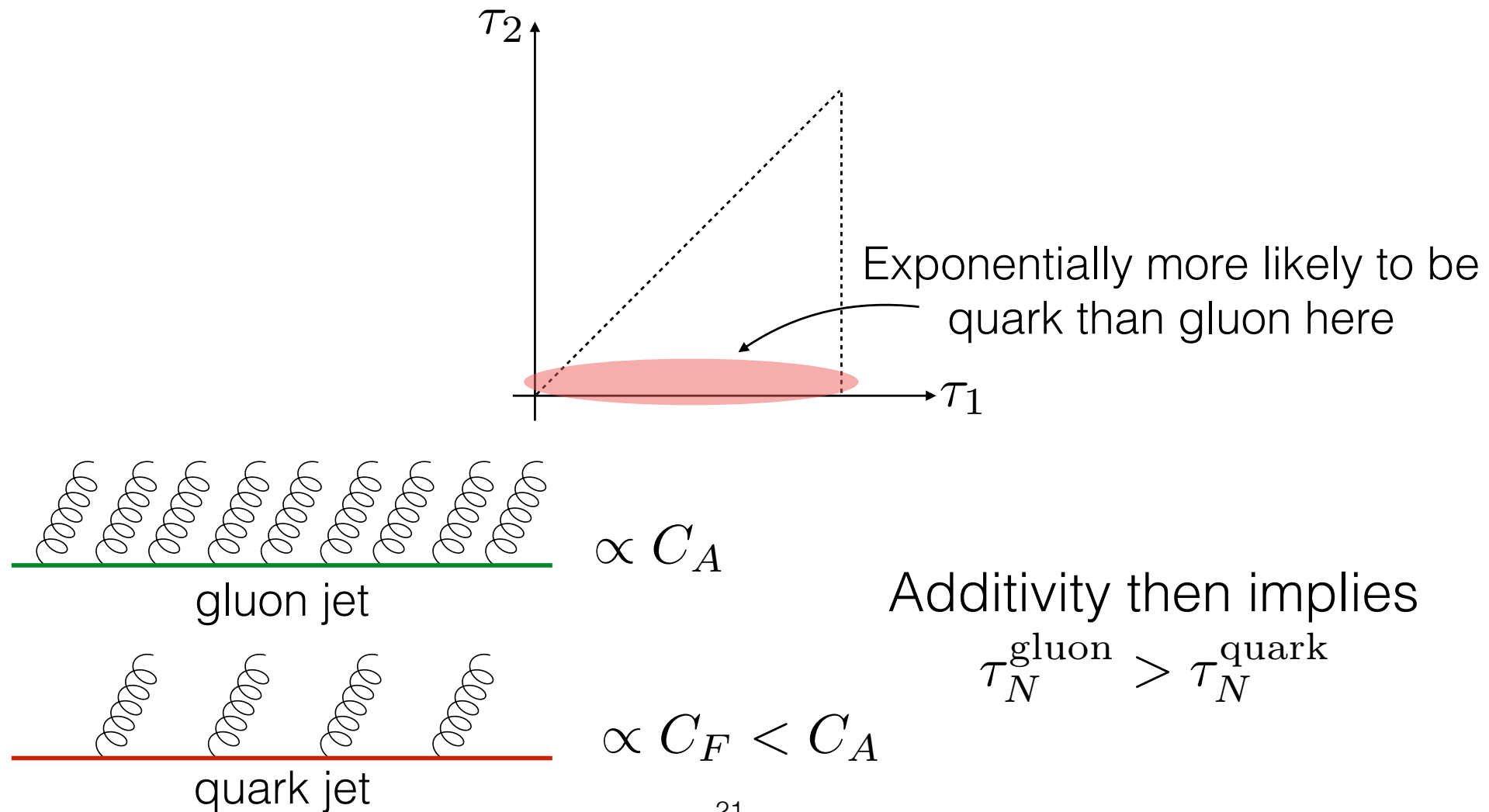
Particle production as Poisson process

IRC safety + additivity = exponential suppression

Exponentially small probability in regions where $\tau_N \rightarrow 0$

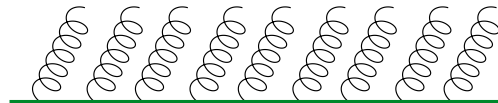
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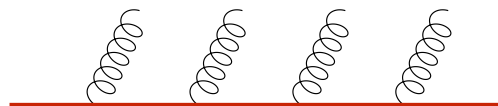
Example 3: The Likelihood for Quark vs. Gluon Discrimination

Problem:



gluon jet

vs.



quark jet

1st dumb thing:

Most naive results from stats/ML

Universal Approx.

Theorem

Cybenko 1989, etc

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Neyman-Pearson

Lemma

Neyman, Pearson 1933

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2nd dumb thing:

IRC safe observables have a

Sudakov form factor

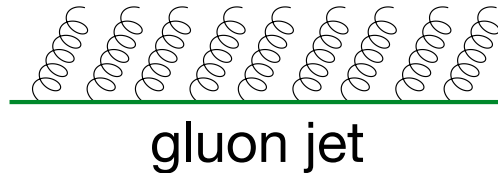
$$p_g(\{x_i\}) \sim e^{-C_A f(\{x_i\})}$$

$$p_q(\{x_i\}) \sim e^{-C_F f(\{x_i\})}$$

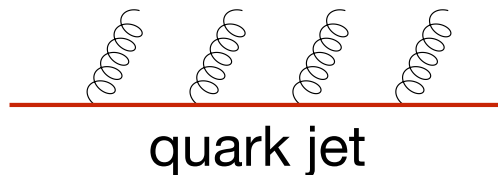
Vanishes exponentially in the soft/
collinear limits; $C_A > C_F$

Example 3: The Likelihood for Quark vs. Gluon Discrimination

Problem:



vs.



Consequences:

Likelihood is IRC safe

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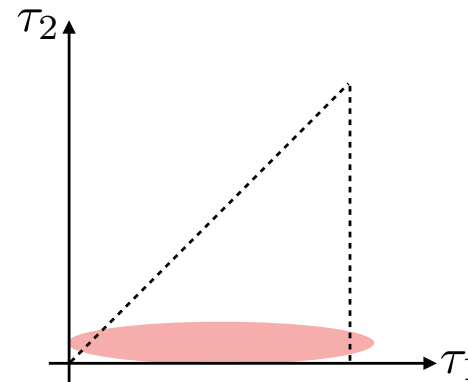
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$$p_g(\{x_i\}) \sim e^{-C_A f(\{x_i\})}$$

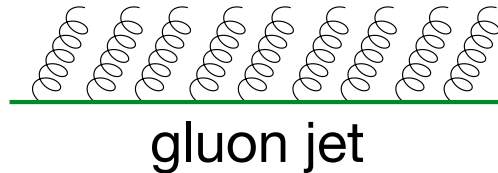
$$p_q(\{x_i\}) \sim e^{-C_F f(\{x_i\})}$$



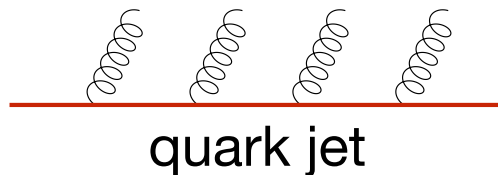
Entire singular region is mapped to the unique value $L = 0$

Example 3: The Likelihood for Quark vs. Gluon Discrimination

Problem:



vs.



Consequences:

Explains why IRC safe observables are good q/g discriminants

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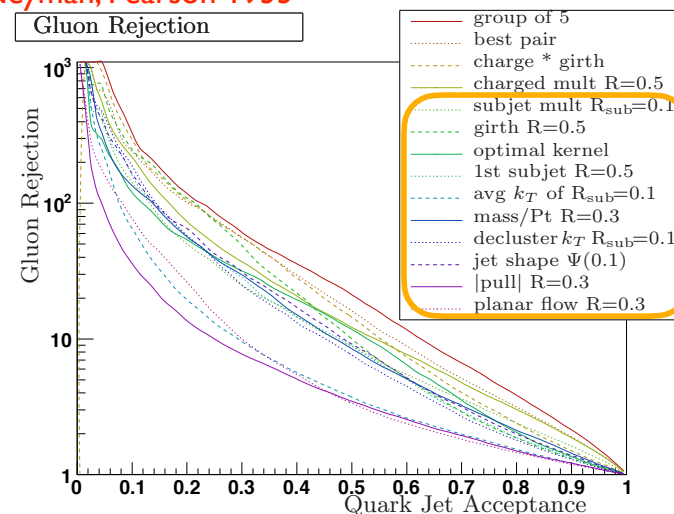
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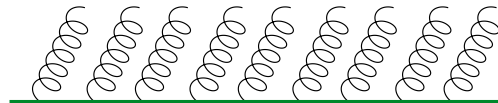
$$p_q(\{x_i\}) \sim e^{-C_F f(\{x_i\})}$$

Simplify the work of an NN and give it IRC safe inputs



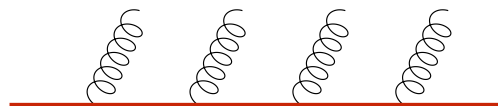
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Sudakov form factor

$$p_g(\{x_i\}) \sim e^{-C_A f(\{x_i\})}$$

$$p_q(\{x_i\}) \sim e^{-C_F f(\{x_i\})}$$

IRC safe optimality validated in explicit NN implementation

TABLE III. Comparison of the quark-gluon classification performance of EFN and PFN networks, via AUC, on jets with no hadronization effects included.

Jet p_T Range	EFN	PFN	$\Delta(\text{PFN-EFN})$
200-220 GeV	0.739 ± 0.001	0.737 ± 0.001	-0.002 ± 0.002
500-550 GeV	0.753 ± 0.001	0.750 ± 0.001	-0.003 ± 0.002
1000-1100 GeV	0.759 ± 0.001	0.758 ± 0.001	-0.001 ± 0.002

arXiv:2103.09103

It is our job as physicists to make sure we understand the problem well so that we can trust machine learning to output something sensible