

The Latent Information Geometry of Jet Classification

IRN Terascale @ Heidelberg University 2026

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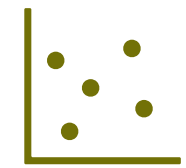
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Motivation

“The Geometry of Decision Making”



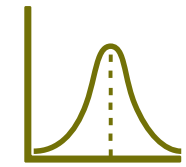
Goal: find a geometric link between a networks classification decision and jet-physics observables.



Setup: Embed high-dimensional jet-data in a low-dimensional latent space, given a task.



Question: Do geometric structures emerge?



Tool: Information geometry!

Three-fold Jet-Tagging

Jet Classes

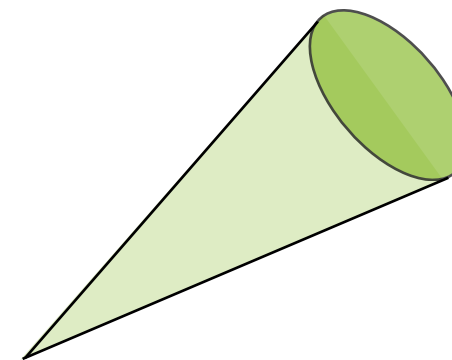
1. q/g - jets
2. Z - jets ($Z \rightarrow q\bar{q}$)
3. t -jets ($t \rightarrow bq\bar{q}'$)

Observables

Jet mass m_{jet}

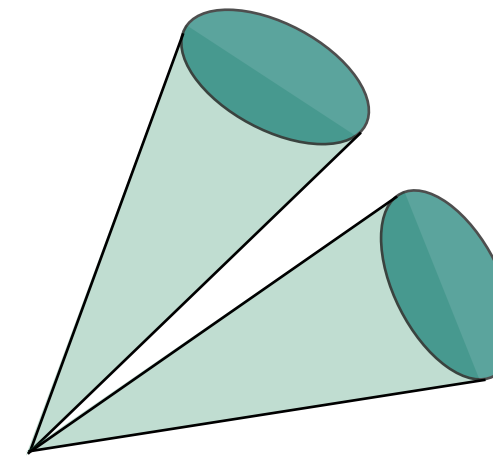
N -subjettiness ratios $\tau_{21} = \frac{\tau_2}{\tau_1}$, $\tau_{32} = \frac{\tau_3}{\tau_2}$

q/g



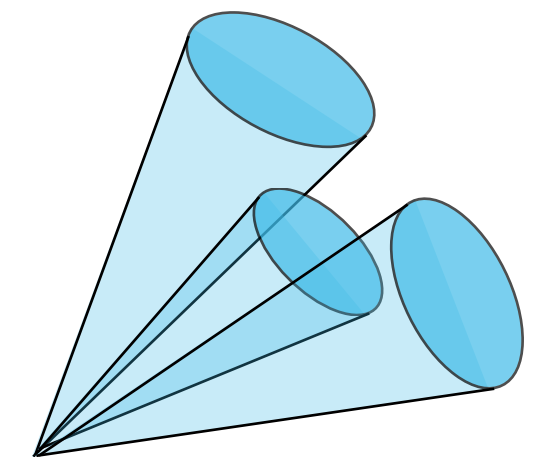
1-prong

$Z \rightarrow q\bar{q}$



2-prong

$t \rightarrow bq\bar{q}'$



3-prong

Setup

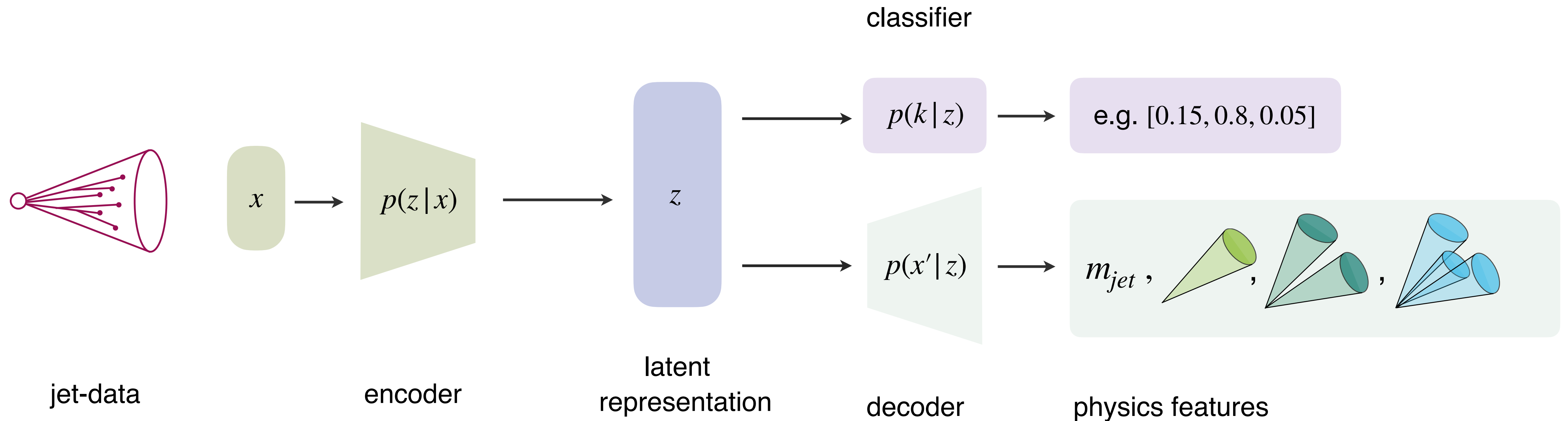
Network and Latent Space

Variational autoencoder (VAE) + classifier

Probability distribution over latent representations $\rightarrow$ continuous sampling

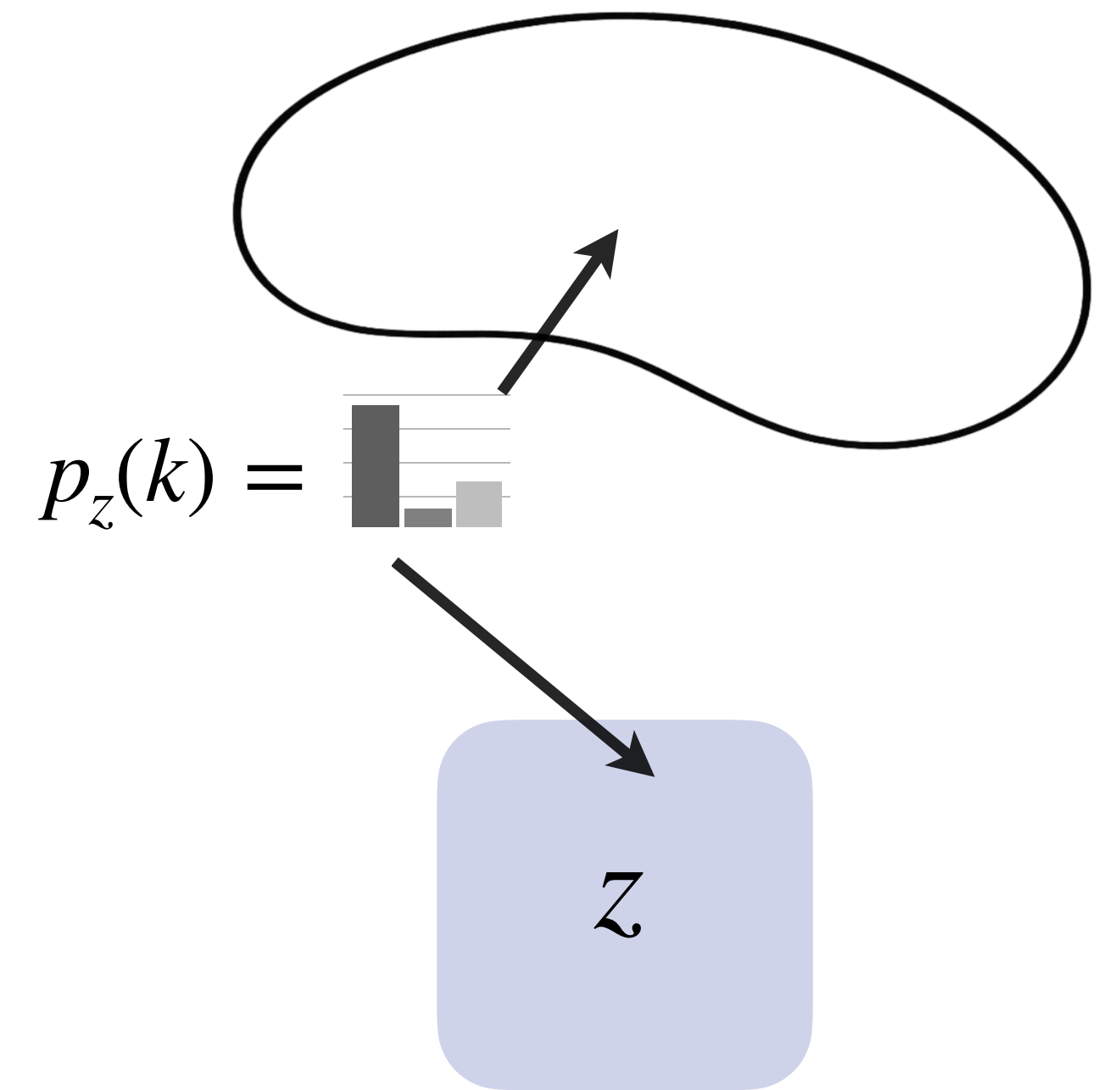
Training: classification, reconstruction, regularization

Regularization + probabilistic network $\rightarrow$ information geometry



Construction of a Latent Information Geometry

Each distribution p_z is identified with a point on a **statistical manifold**

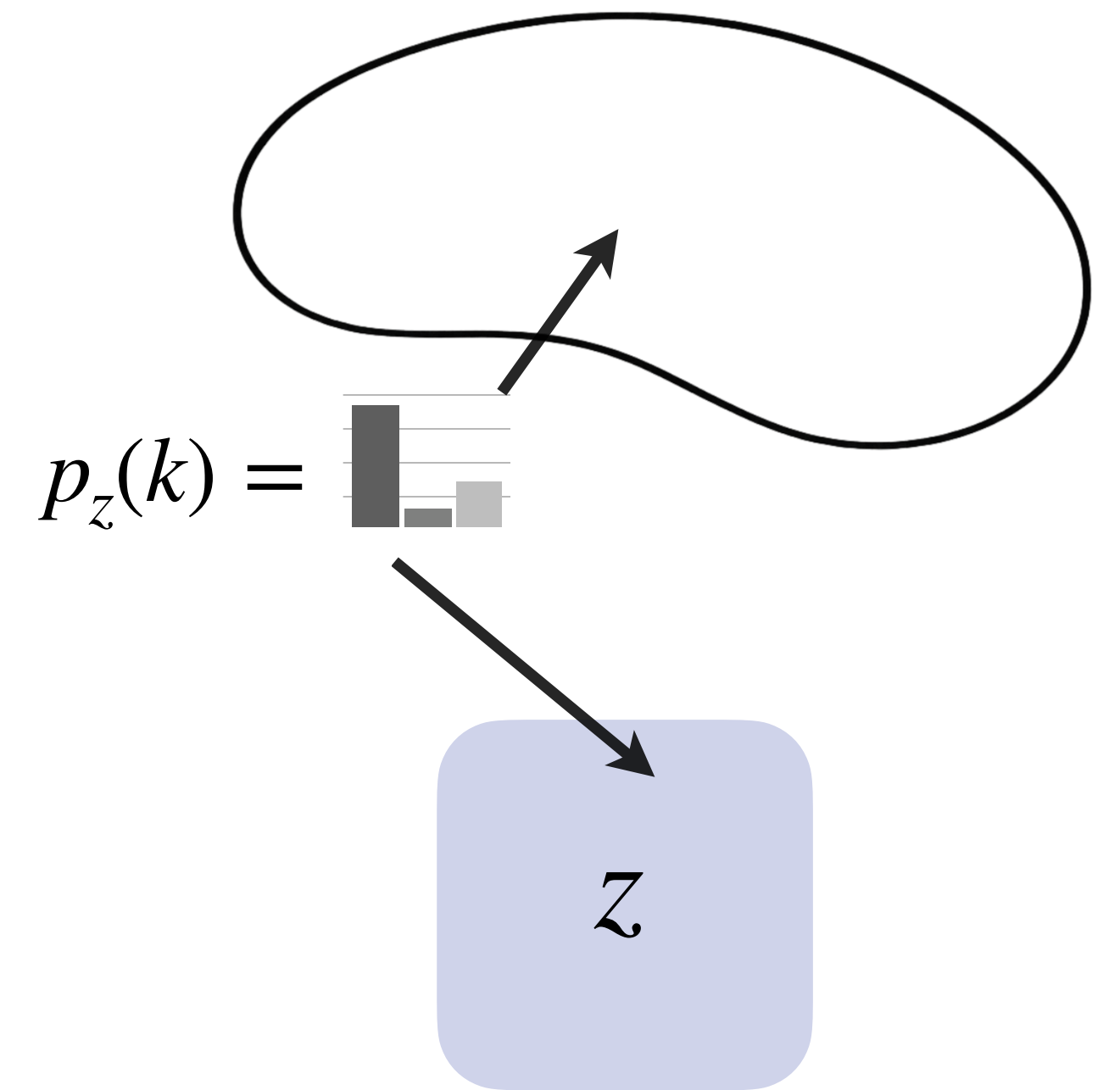


Geometry I

Construction of a Latent Information Geometry

Each distribution p_z is identified with a point on a **statistical manifold**

Latent $\{z^i\}$ are a special, learned coordinate frame

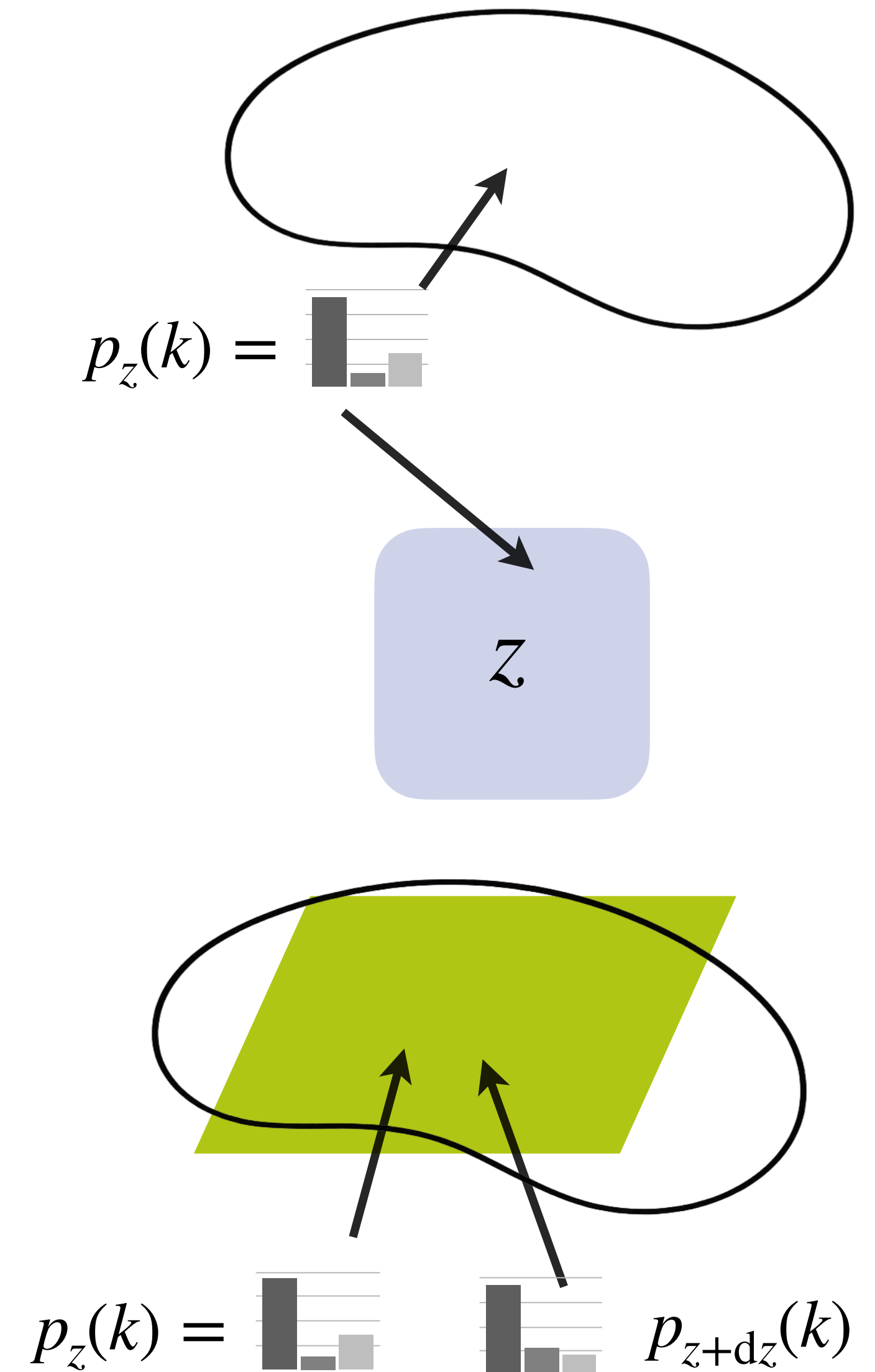


Construction of a Latent Information Geometry

Each distribution p_z is identified with a point on a **statistical manifold**

Latent $\{z^i\}$ are a special, learned coordinate frame

Fisher information metric $F_{ij}(z) = \mathbb{E}_{p_z}[\partial_i \log p_z \partial_j \log p_z]$, $\partial_i \equiv \frac{\partial}{\partial z^i}$



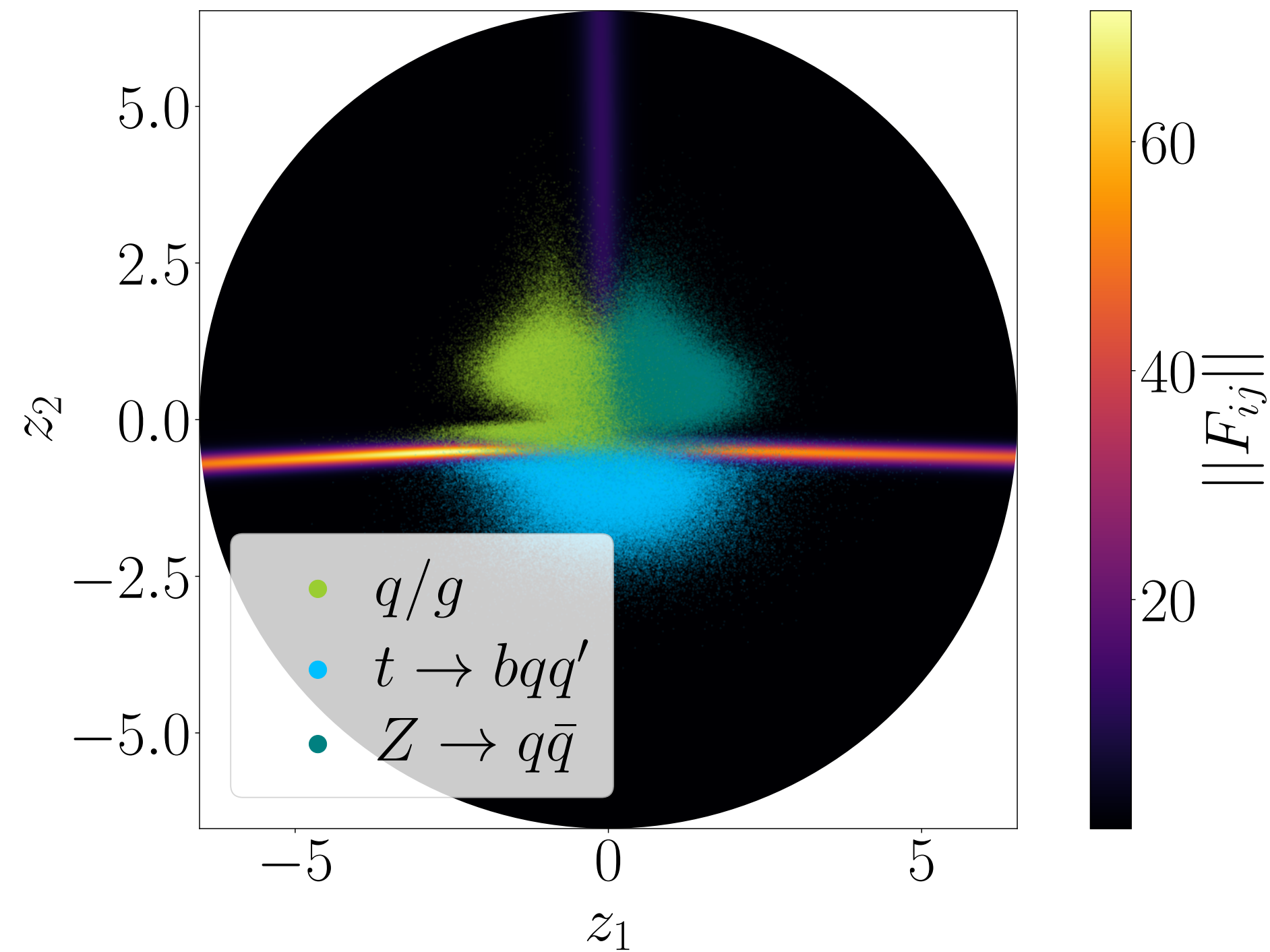
Geometry II

Classifier Fisher information

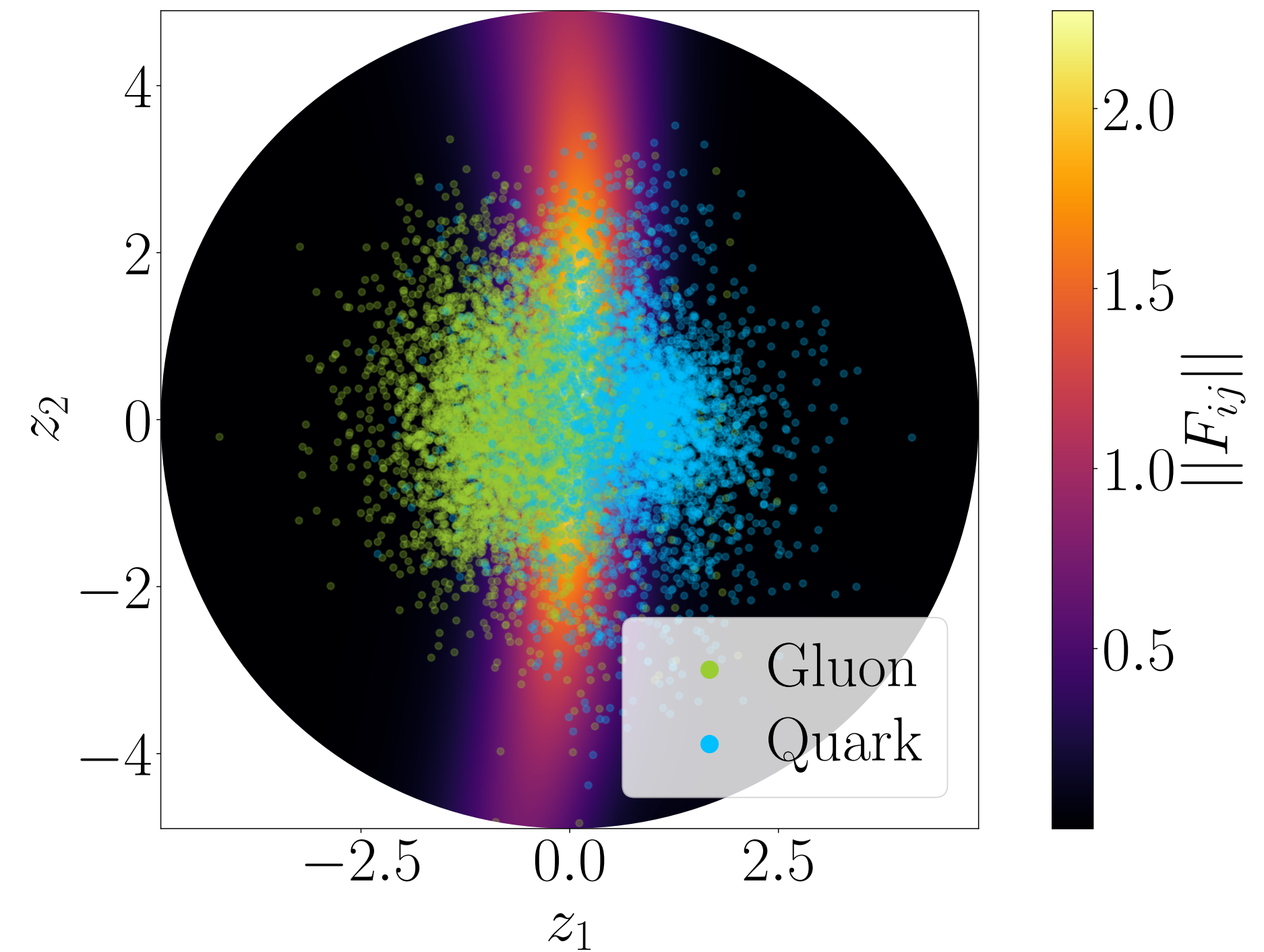
Fisher norm $\|F_{ij}\| = \sum F_{ij} F_{ij}$

Local measure of event distinguishability / classifier sensitivity.

Three-Class

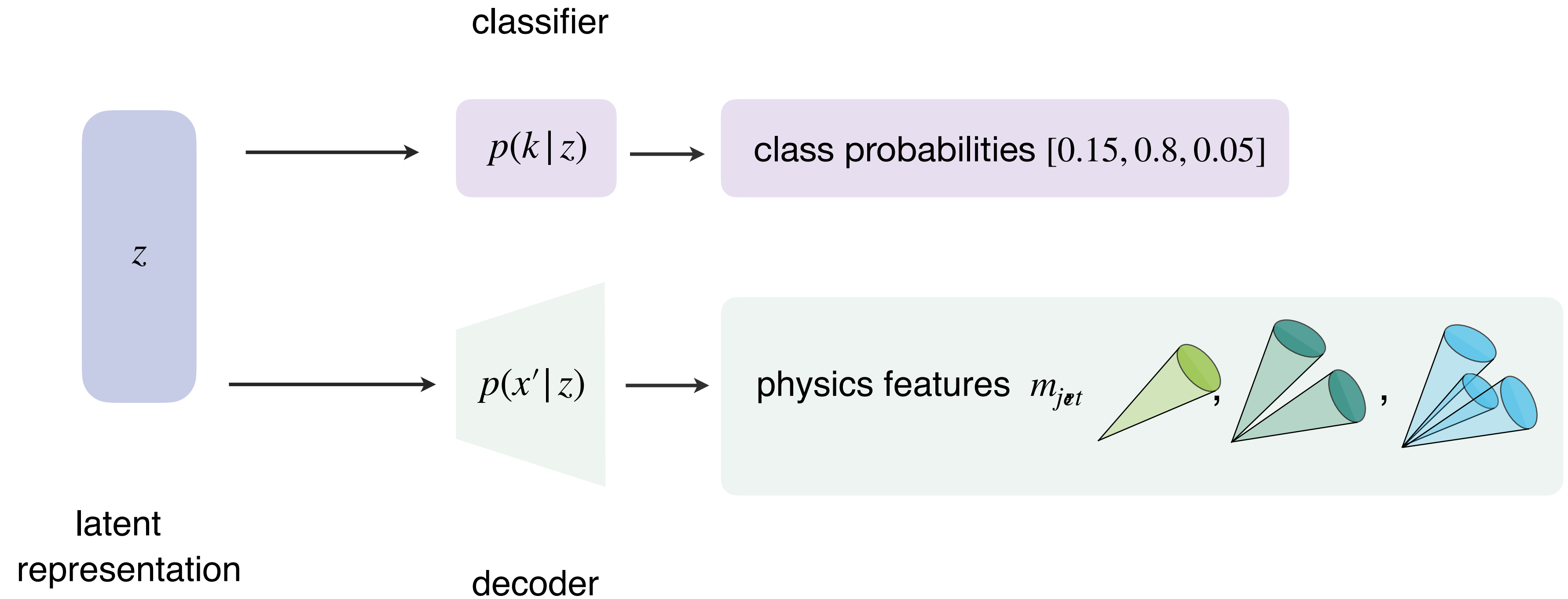


Binary



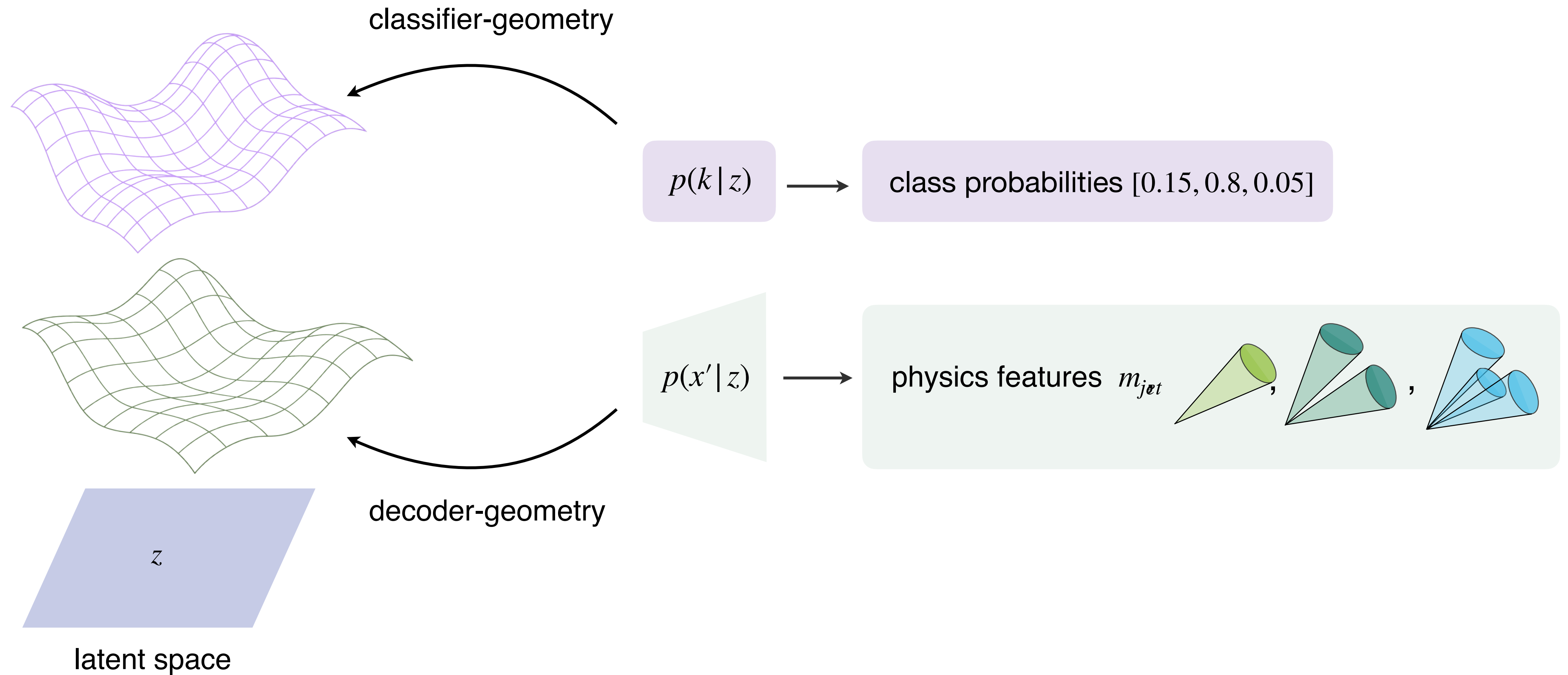
Two geometries I

Classifier vs. Decoder Geometry



Two geometries I

Classifier vs. Decoder Geometry



Two geometries II

Geometric Link between Classifier and Decoder

Leading Observable

- A. Most sensitive direction of classifier metric
- B. Directional derivative of reconstructed feature

$$D_v\mu(z) = \partial_\lambda\mu(z + \lambda v)|_{\lambda=0}$$

↪ Which observable most effectively changes classifier outcome?

Two geometries II

Geometric Link between Classifier and Decoder

Leading Observable

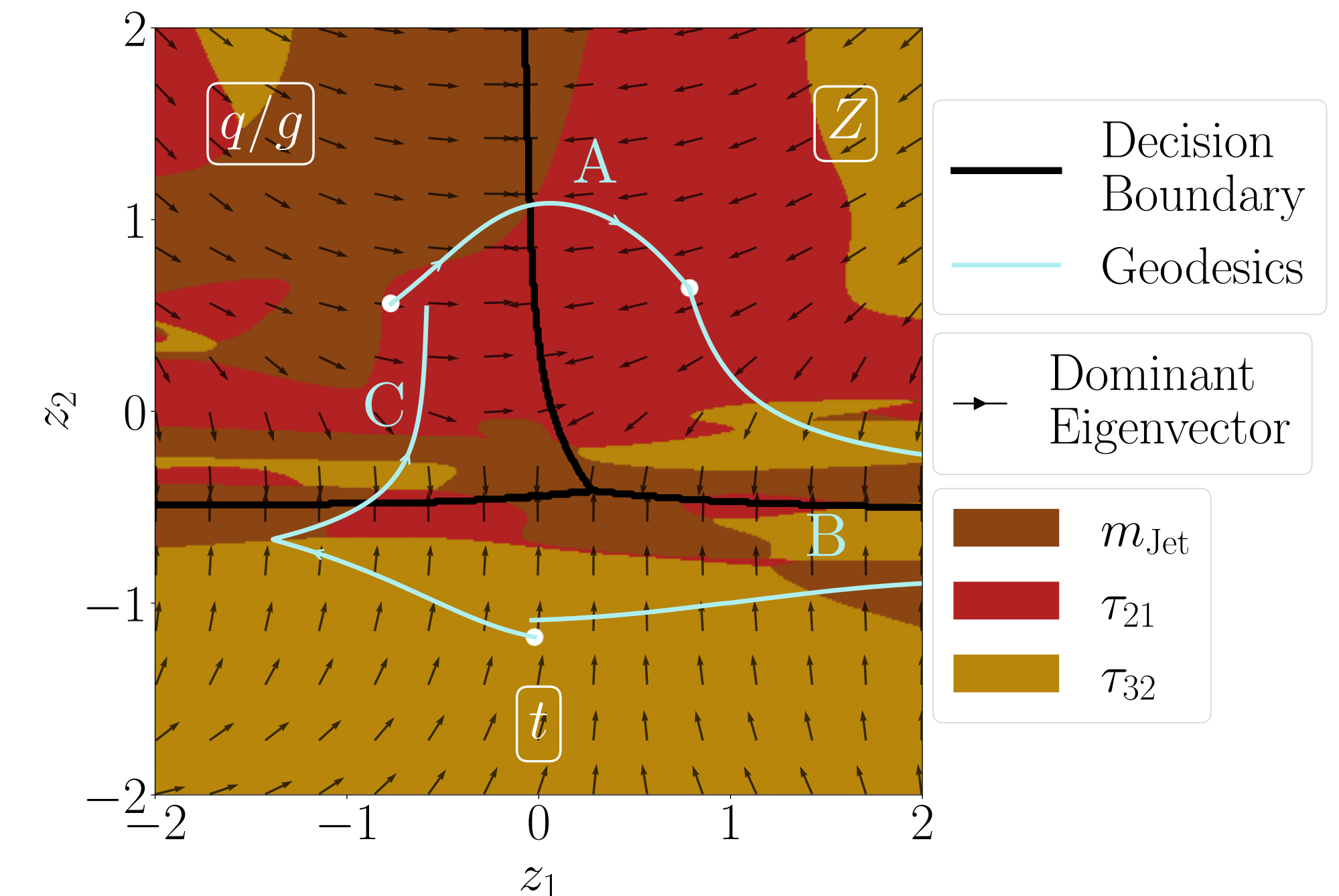
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$$D_v \mu(z) = \partial_\lambda \mu(z + \lambda v) \big|_{\lambda=0}$$

↪ Which observable most effectively changes classifier outcome?

Is interpretable physics reflected in the classifier geometry?

Class distinction visible in feature geometry?



↪ Mostly, τ_{21} is the decisive feature in q/g vs. Z

→ **Beyond Second-Order information**

Geometry IV

Third-Order in the Classifier Geometry

Divergence-Induced Geometry: $D_{\text{KL}}(p_z, p_{z+\text{dz}}) \cong \frac{1}{2} F_{ij}(z) \text{dz}^i \text{dz}^j + \frac{1}{3!} C_{ijk}(z) \text{dz}^i \text{dz}^j \text{dz}^k (+^{(+1)}\Gamma \dots) + \mathcal{O}((\text{dz})^4)$

Third-Order in the Classifier Geometry

Divergence-Induced Geometry: $D_{\text{KL}}(p_z, p_{z+\text{dz}}) \cong \underbrace{\frac{1}{2}F_{ij}(z)\text{dz}^i \text{dz}^j}_{\text{decoder}} + \frac{1}{3!}C_{ijk}(z) \text{dz}^i \text{dz}^j \text{dz}^k \quad (+^{(+1)}\Gamma \dots) + \mathcal{O}((\text{dz})^4)$

Second-order = Riemannian Geometry.

Everything we saw thus far

(Fisher metric, geodesics,...)

Third-Order in the Classifier Geometry

Divergence-Induced Geometry: $D_{\text{KL}}(p_z, p_{z+dz}) \cong \frac{1}{2} F_{ij}(z) dz^i dz^j + \frac{1}{3!} C_{ijk}(z) dz^i dz^j dz^k (+^{(+1)}\Gamma \dots) + \mathcal{O}((dz)^4)$

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Third-Order in the Classifier Geometry

Divergence-Induced Geometry: $D_{\text{KL}}(p_z, p_{z+\text{d}z}) \cong \frac{1}{2}F_{ij}(z)\text{d}z^i \text{d}z^j + \frac{1}{3!}C_{ijk}(z) \text{d}z^i \text{d}z^j \text{d}z^k (+^{(+1)}\Gamma \dots) + \mathcal{O}((\text{d}z)^4)$



Third-order = Nonmetric Geometry

Statistically: skewness-/ Amari-Chentsov tensor: $C_{ijk} = \mathbb{E}_{p_z} \left[\partial_i \log p_z \partial_j \log p_z \partial_k \log p_z \right]$

Classifier Nonmetricity

New: Nonmetricity scalars

E.g. full contraction $C_1 = C_{ijk}C^{ijk}$

Inspiration: metric affine gravity, Weyl gravity.

Classifier Nonmetricity

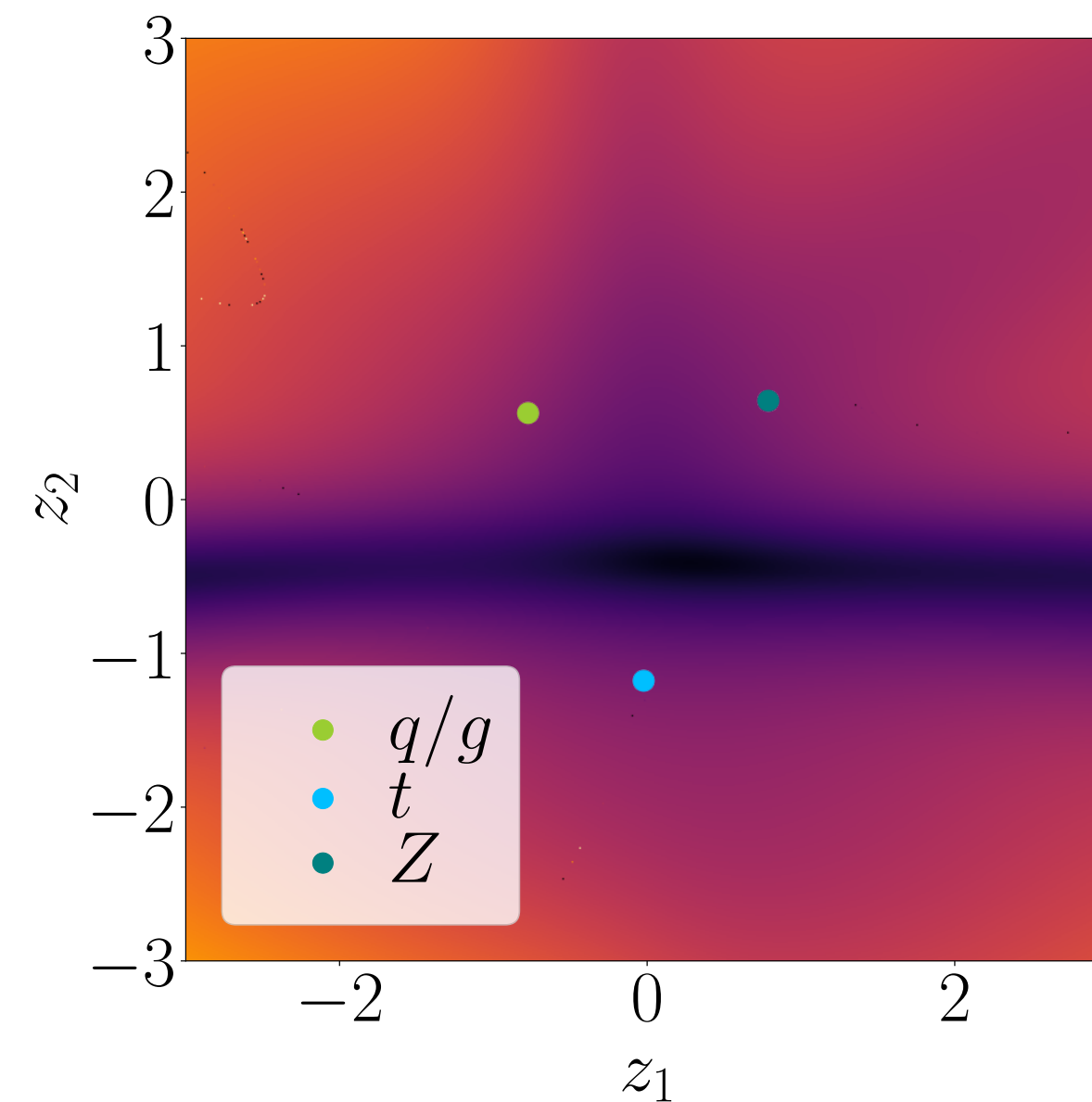
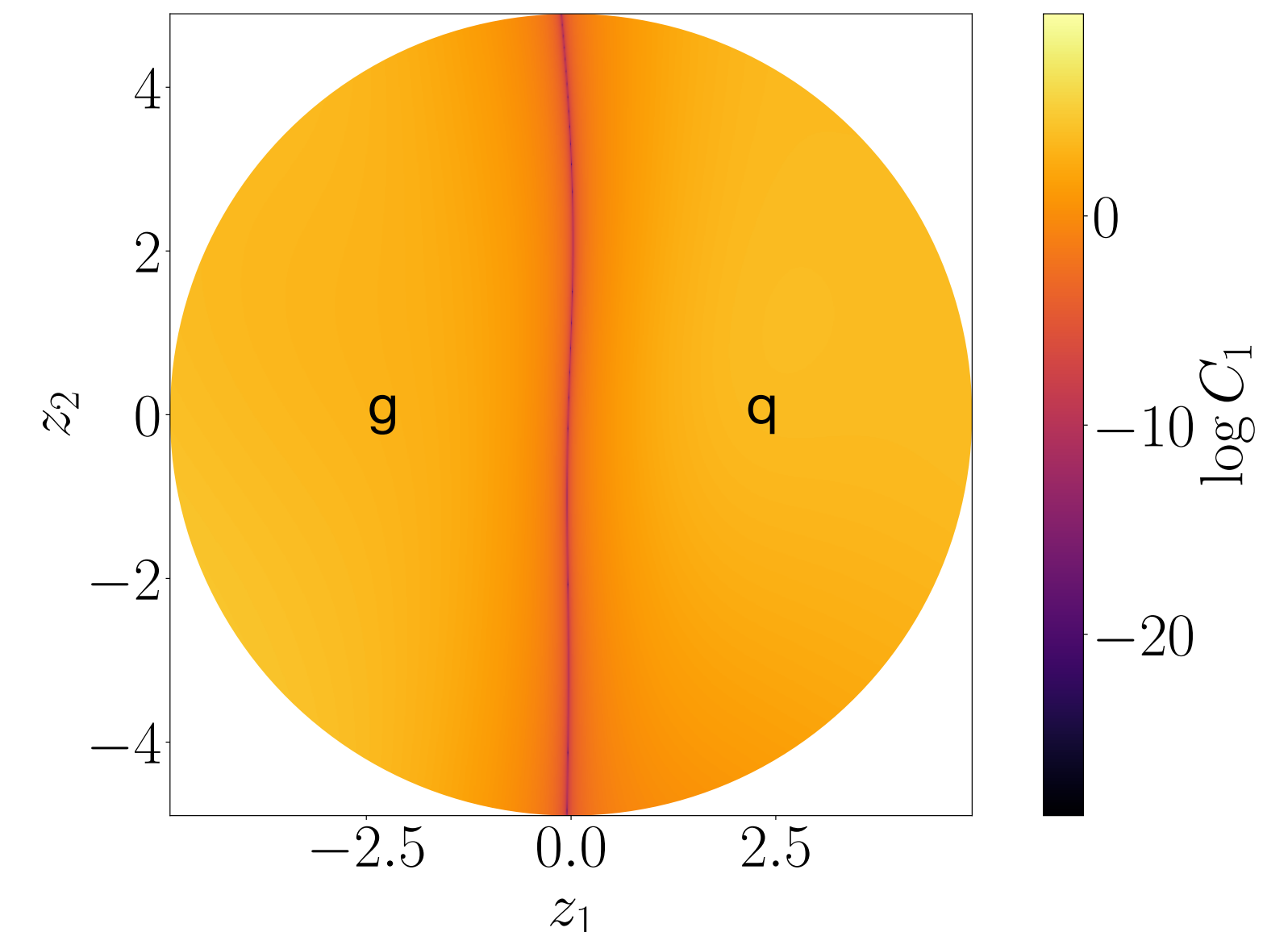
New: Nonmetricity scalars

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Inspiration: metric affine gravity, Weyl gravity.

Different aspect of the classifier decision ✓

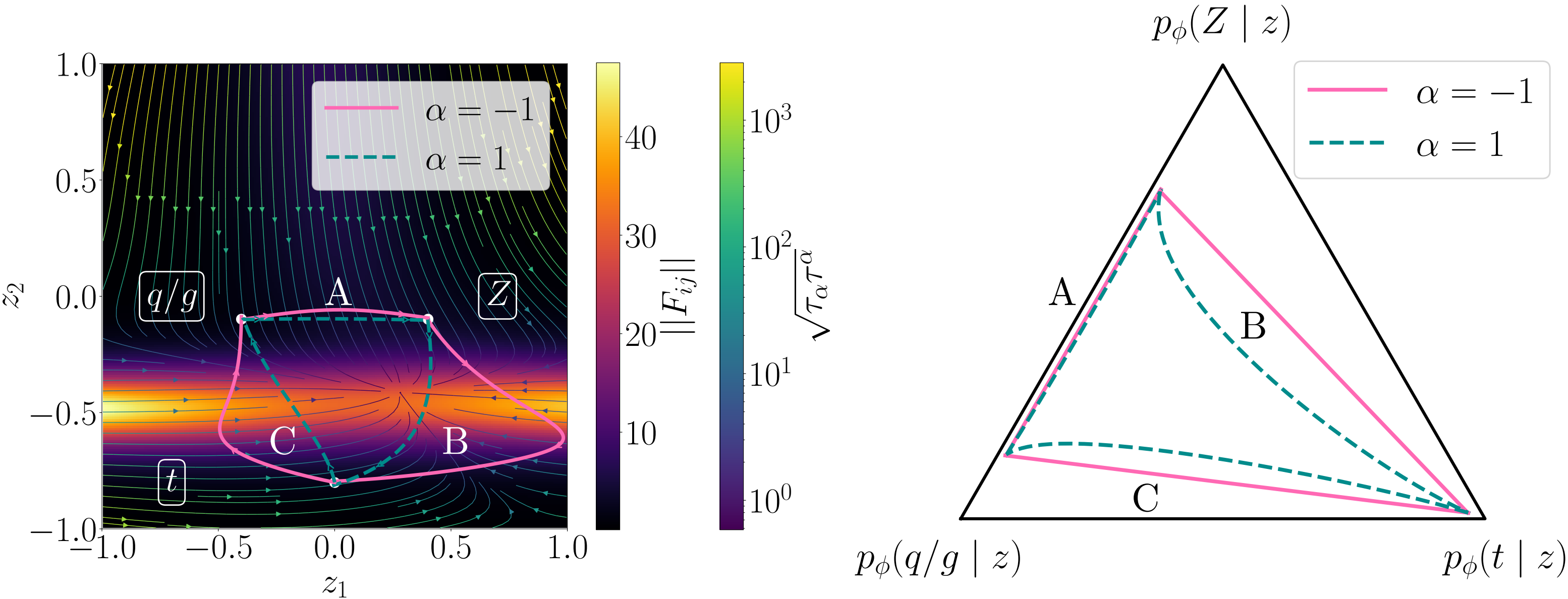
Coordinate-invariant ✓



“On average, how asymmetric is the pull coming from the different classes?”

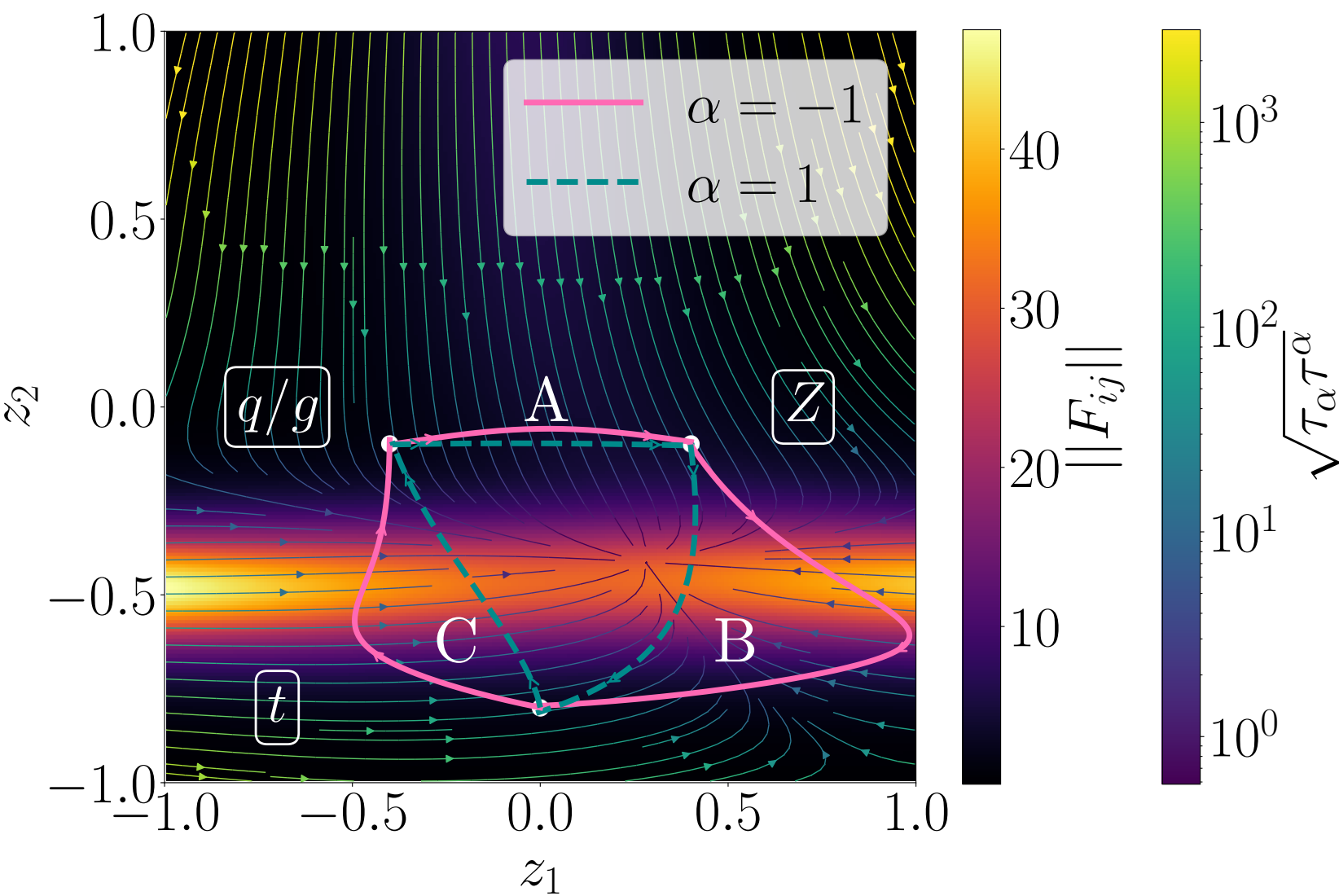
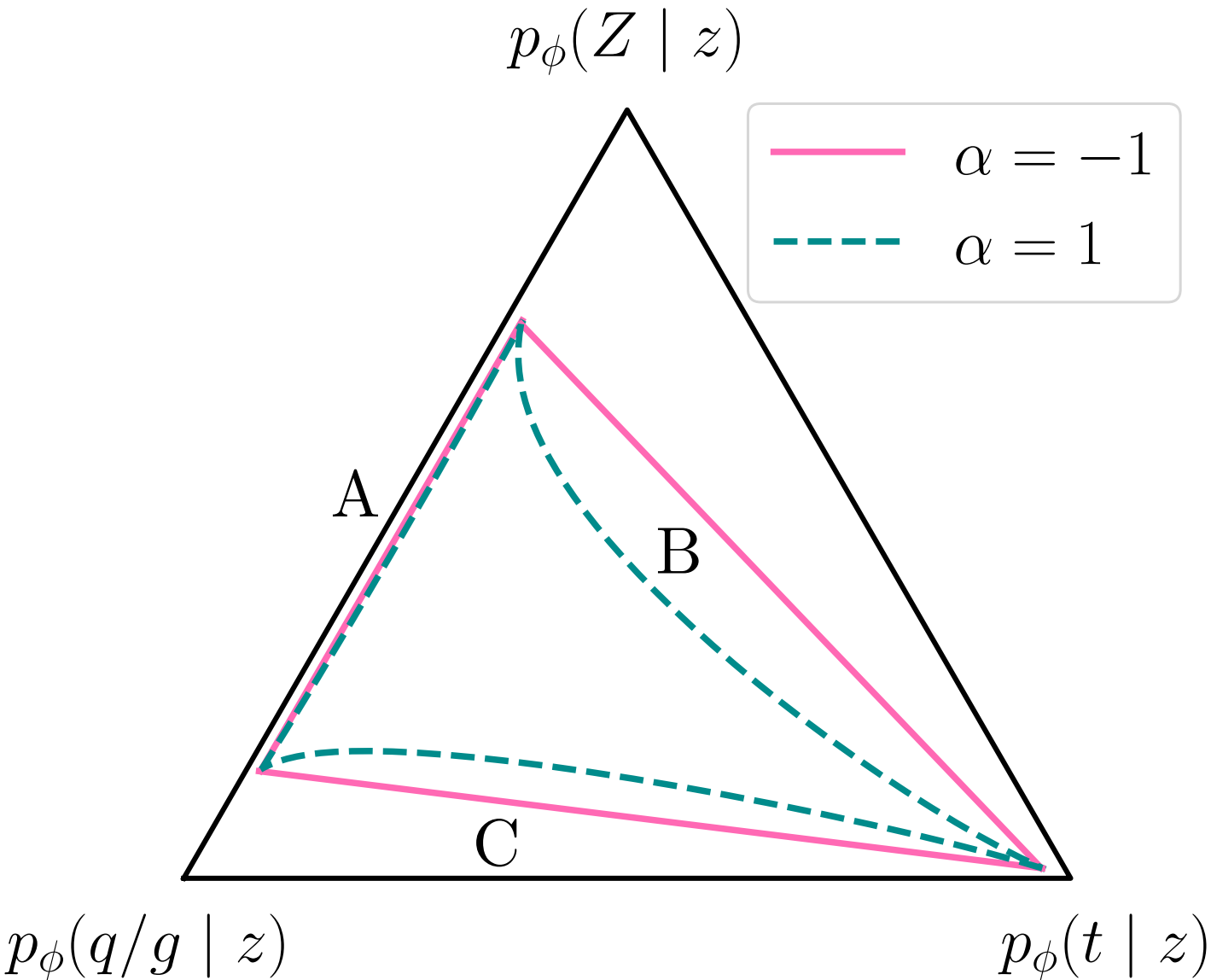
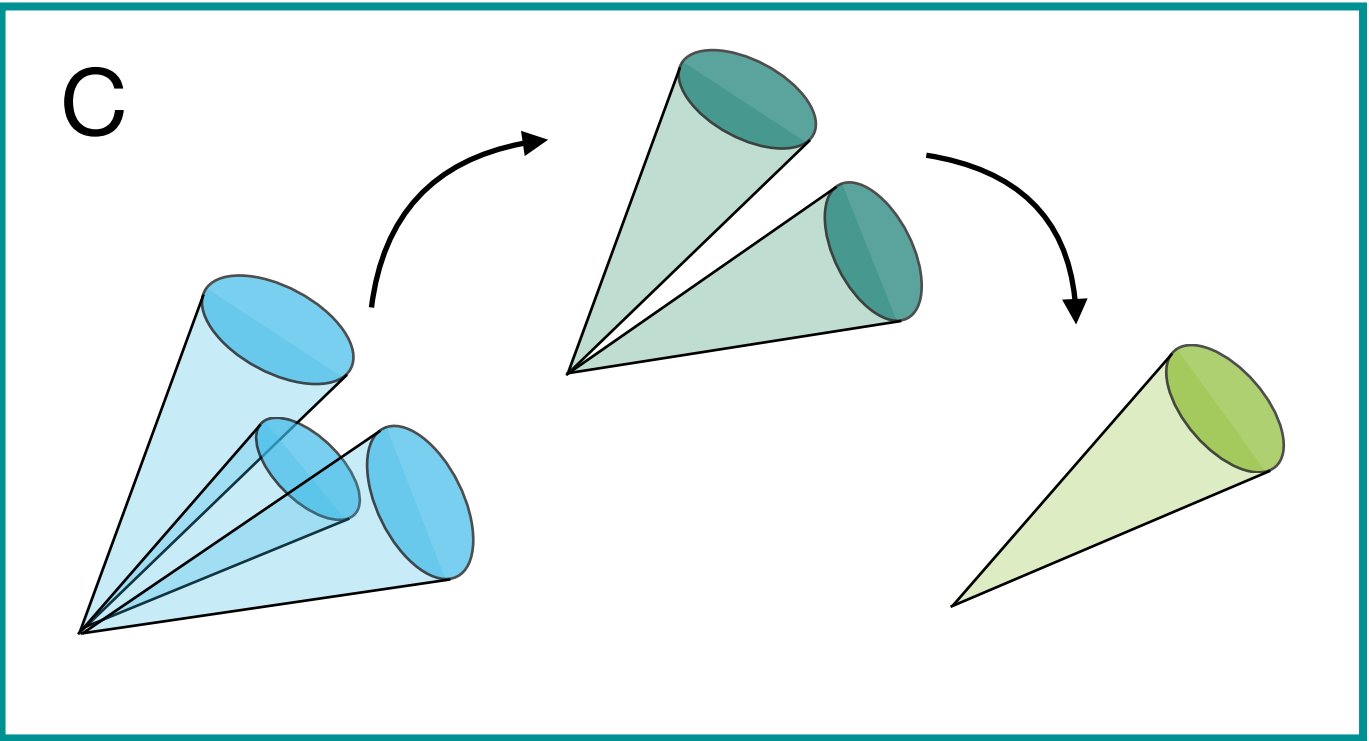
Geometry VI

Two Interpretable Paths



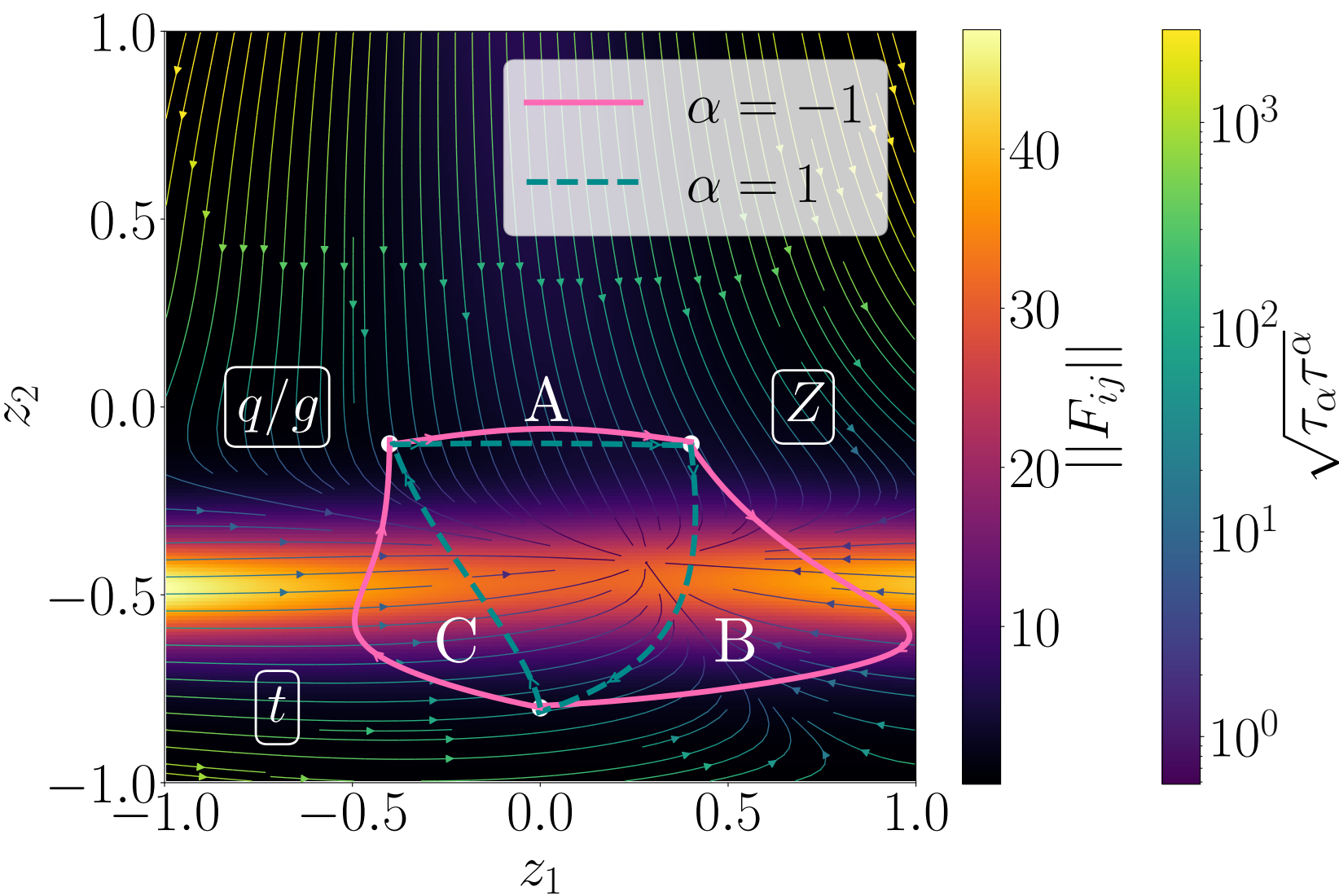
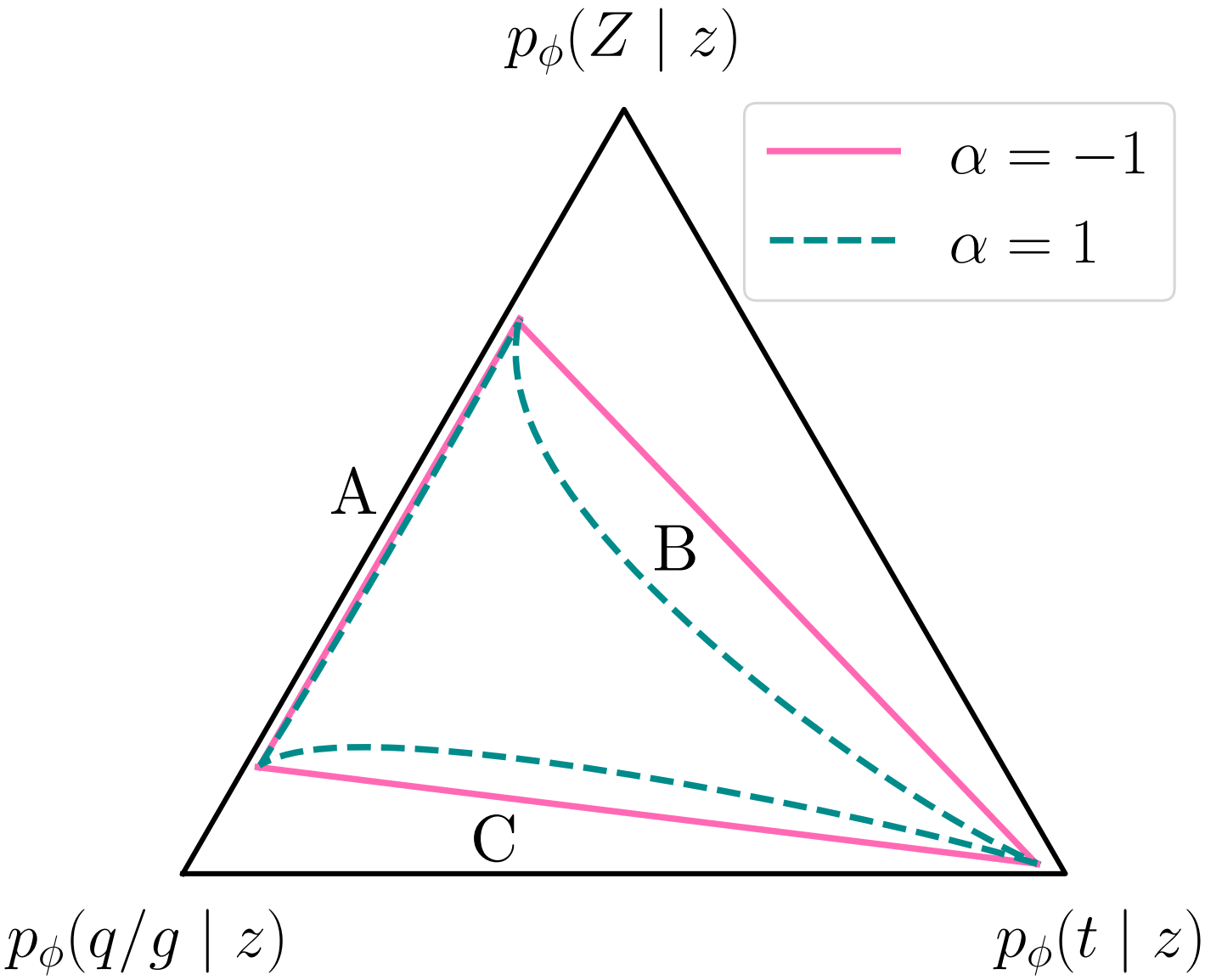
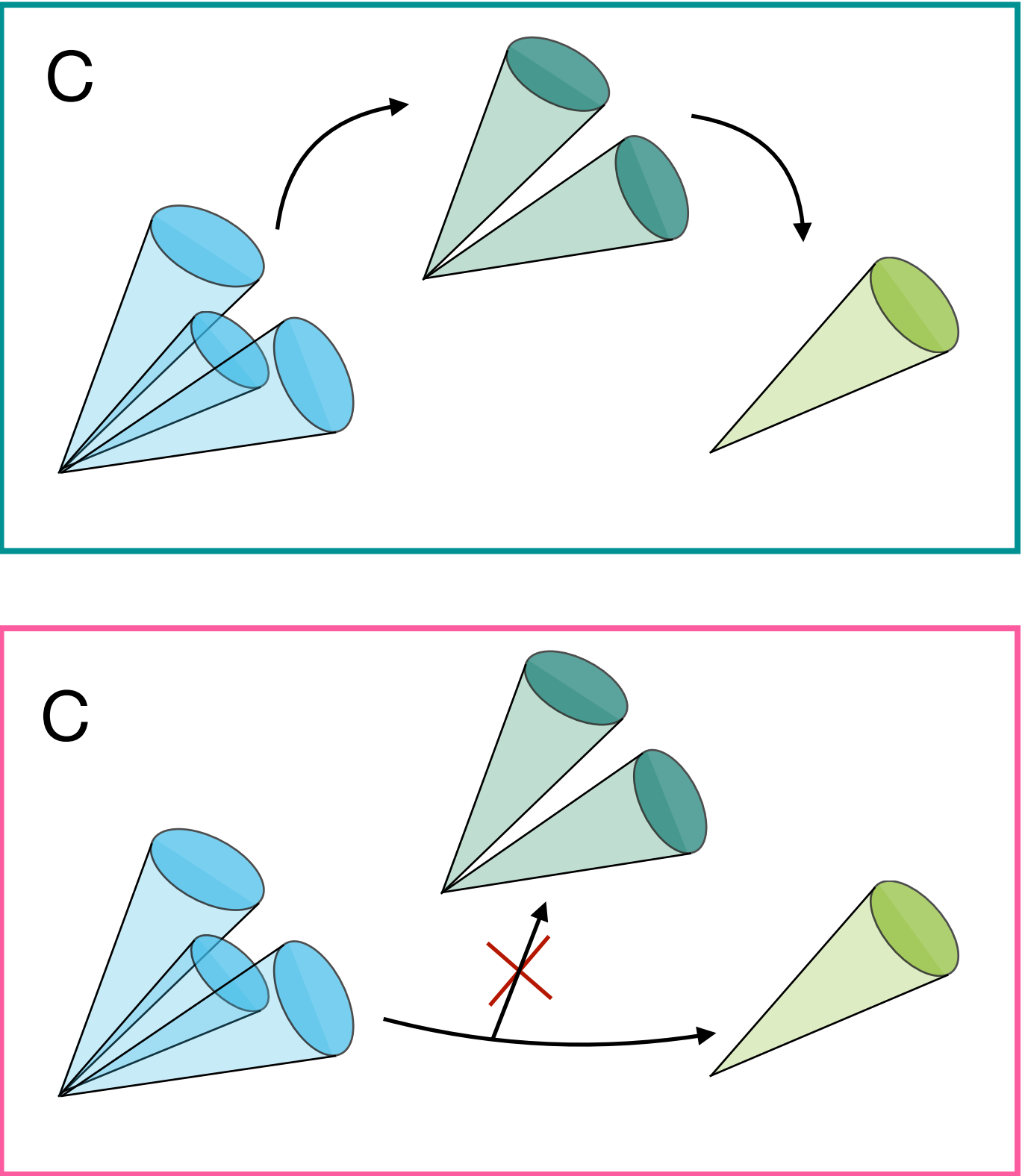
Geometry VI

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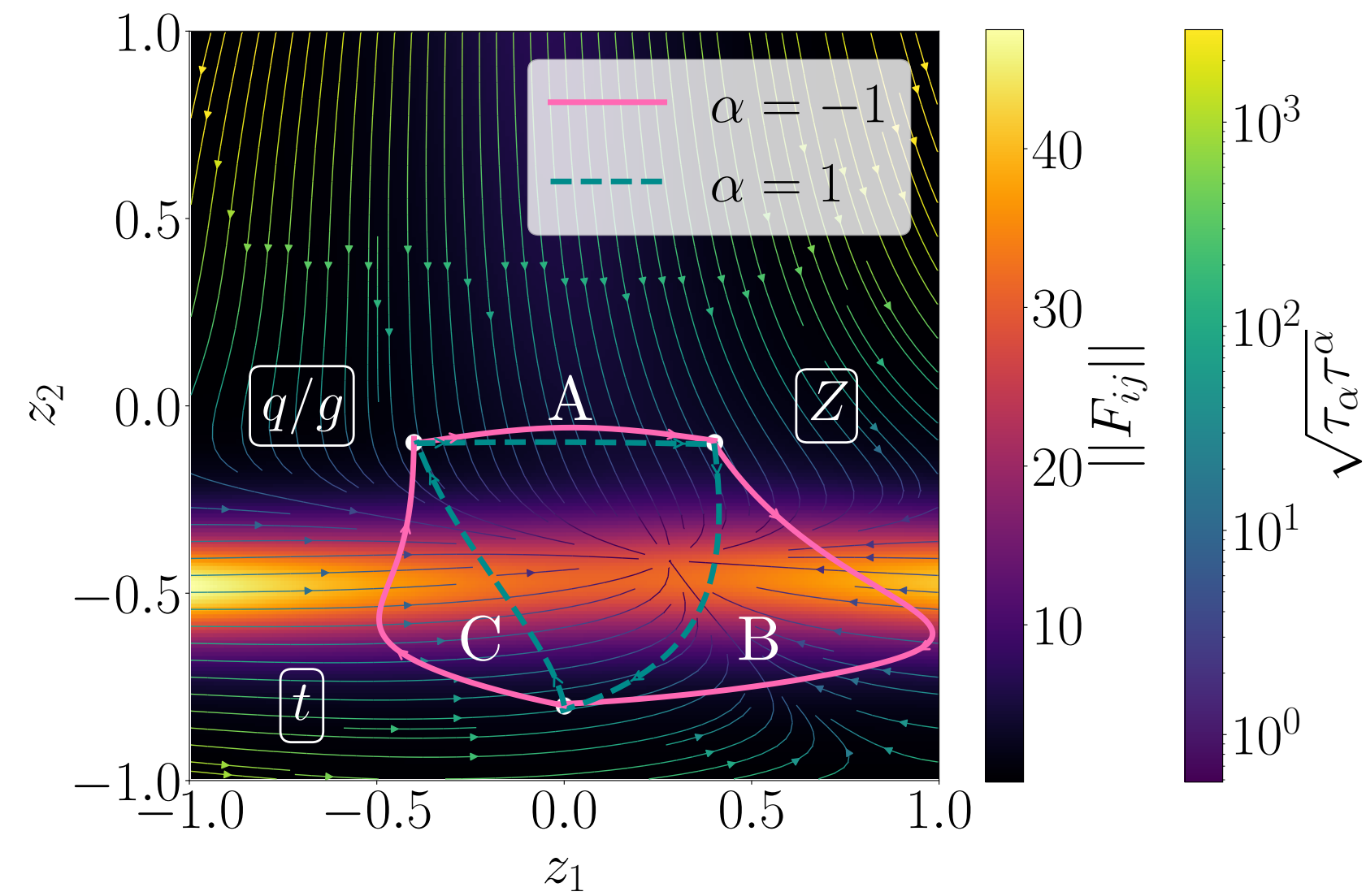
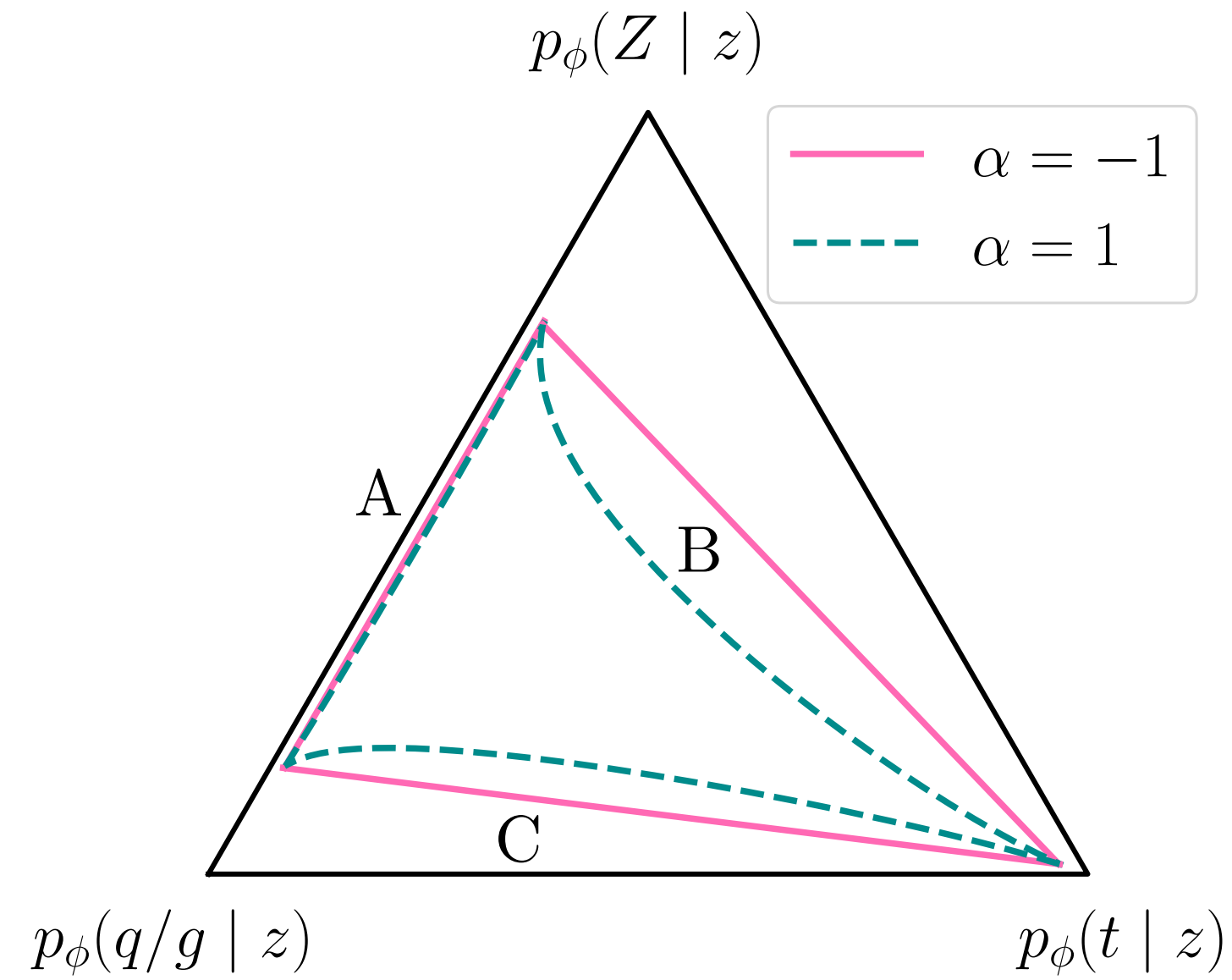
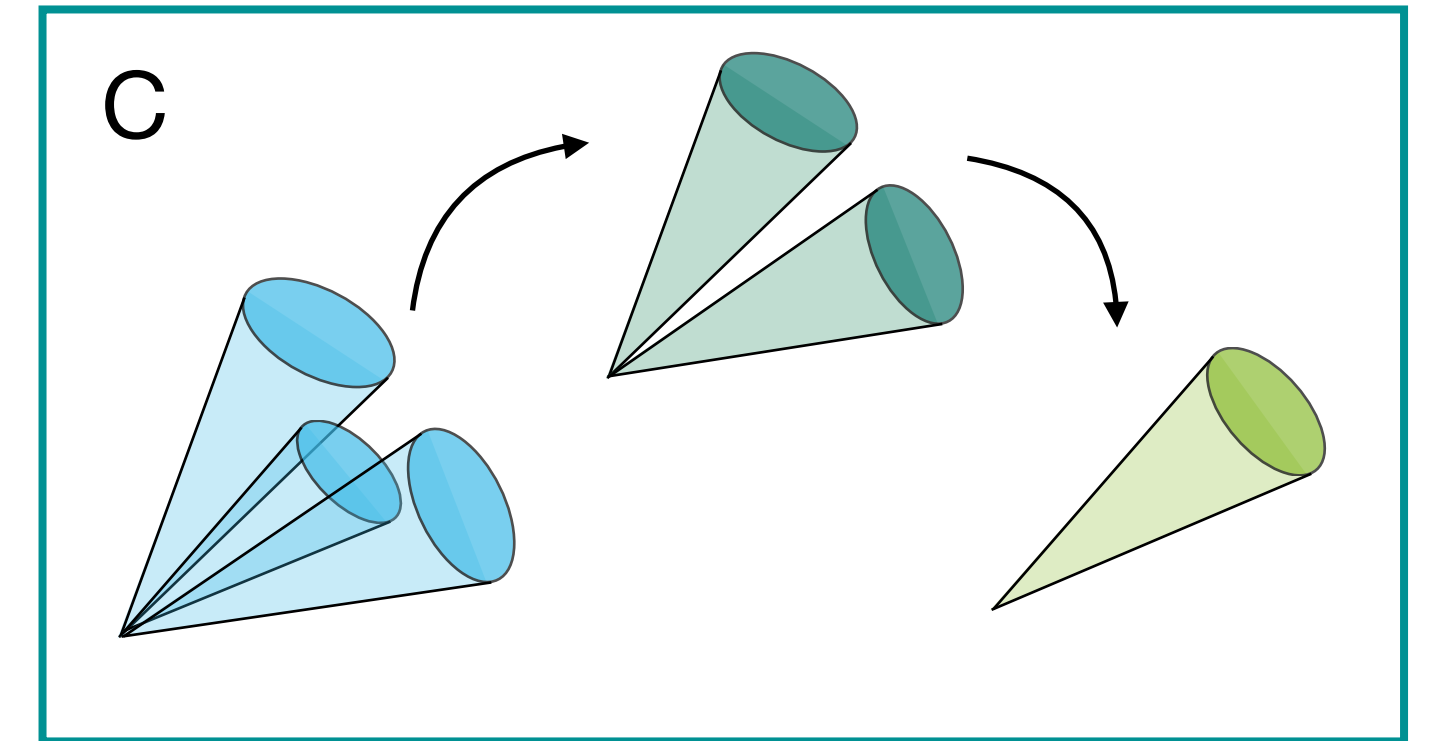
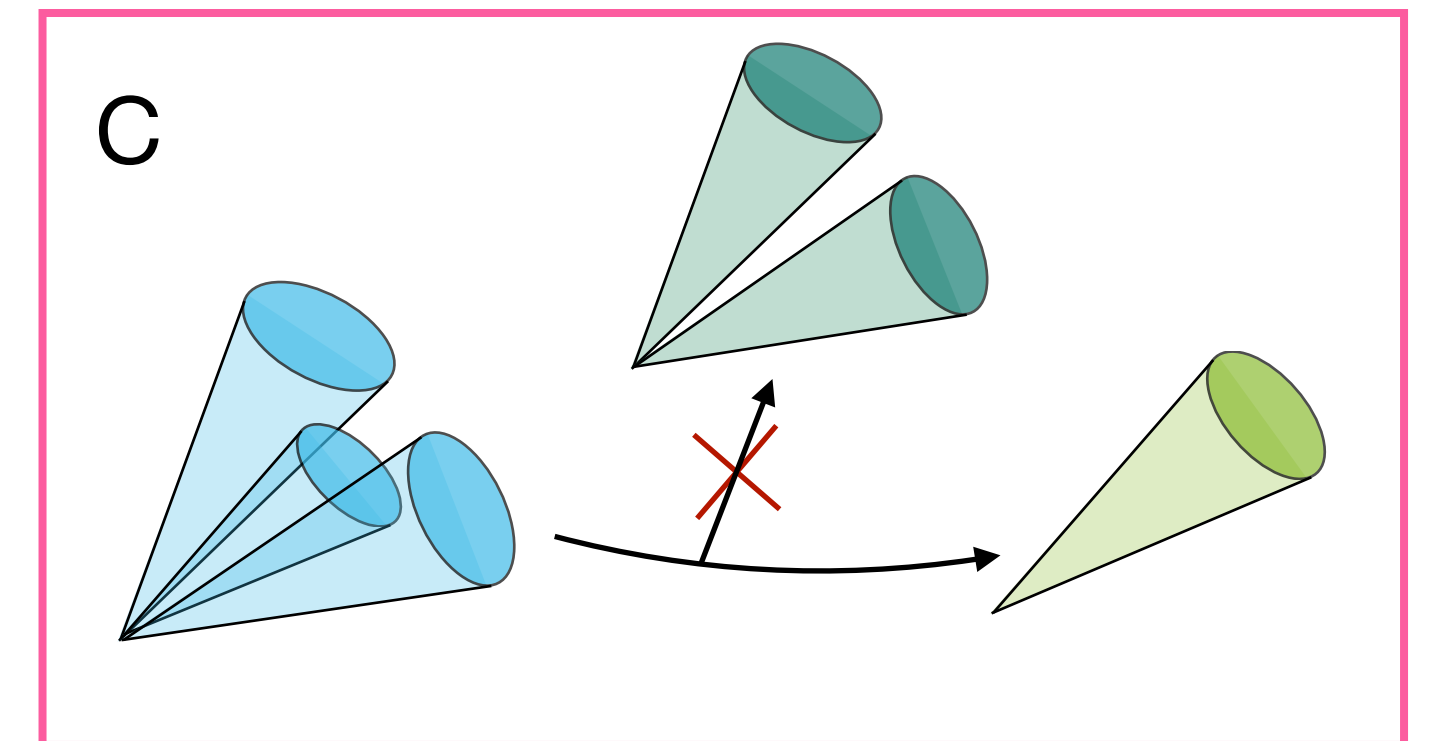
Geometry VI

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Geometry VI

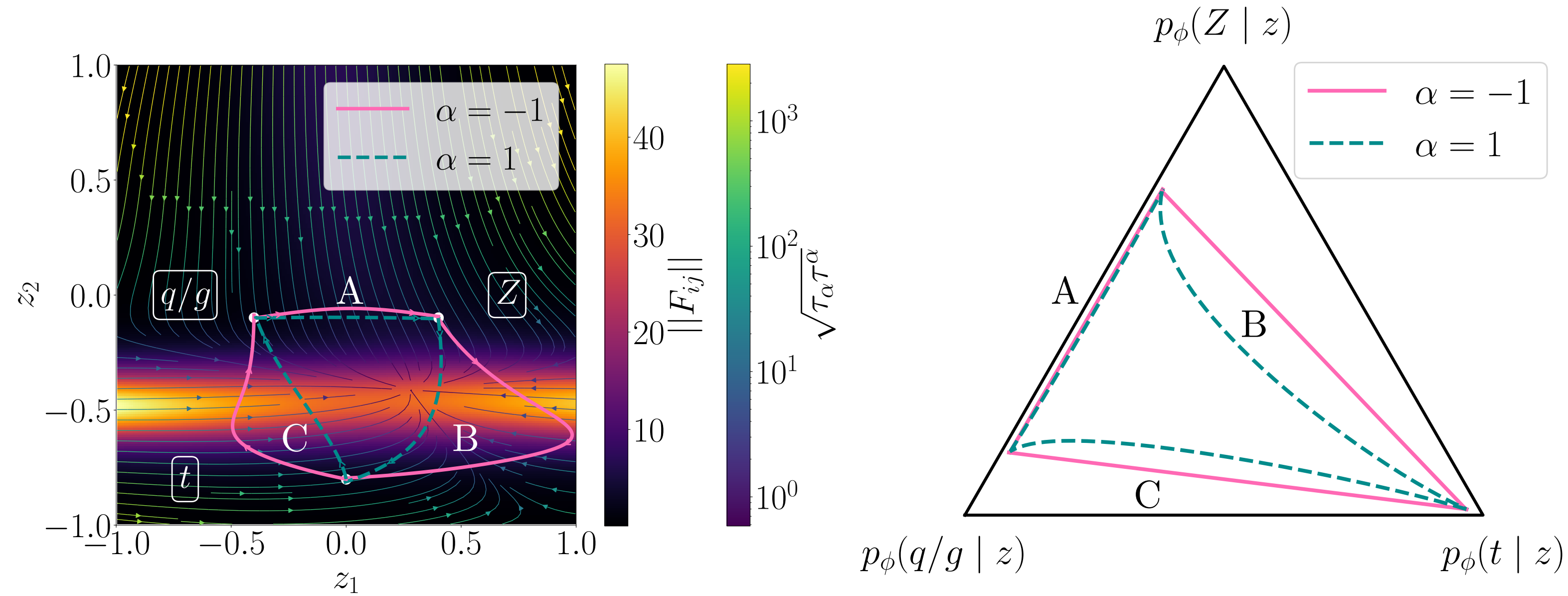
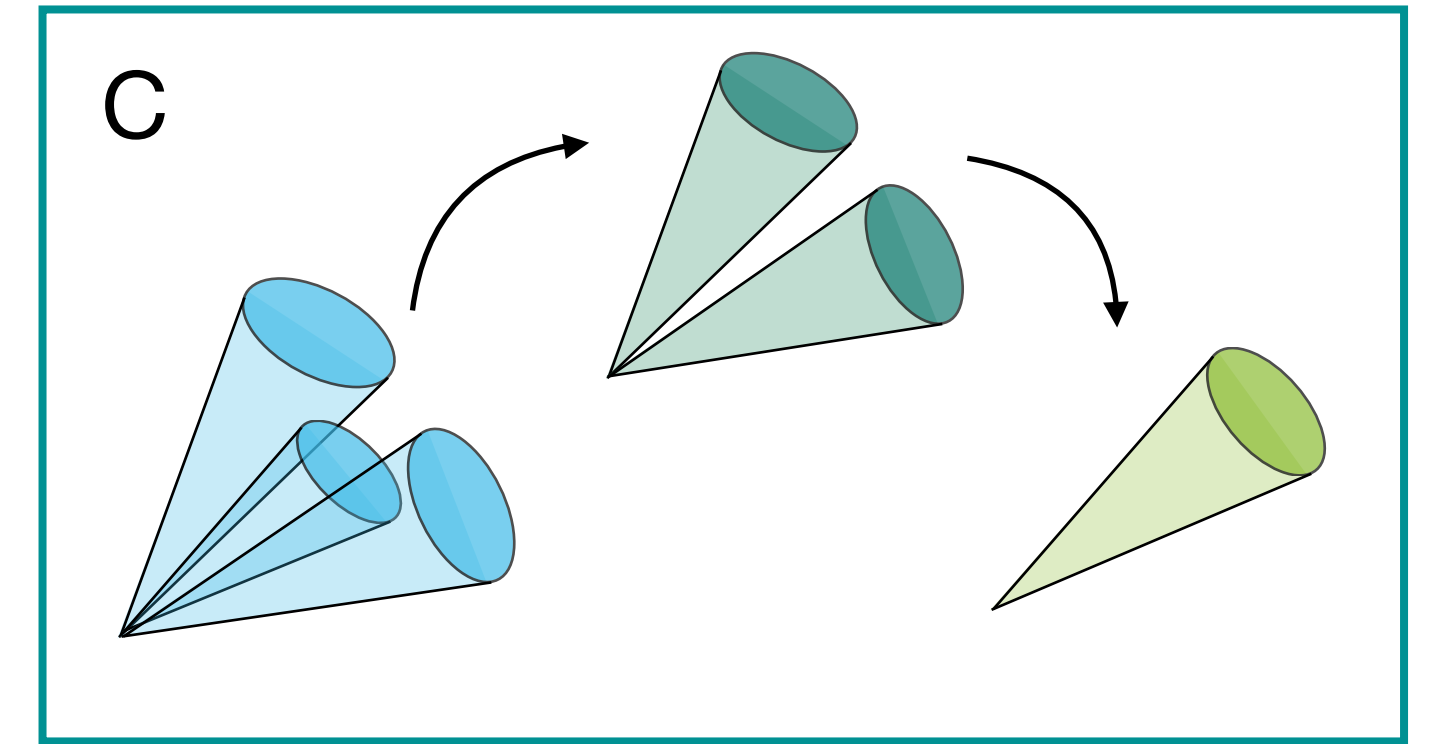
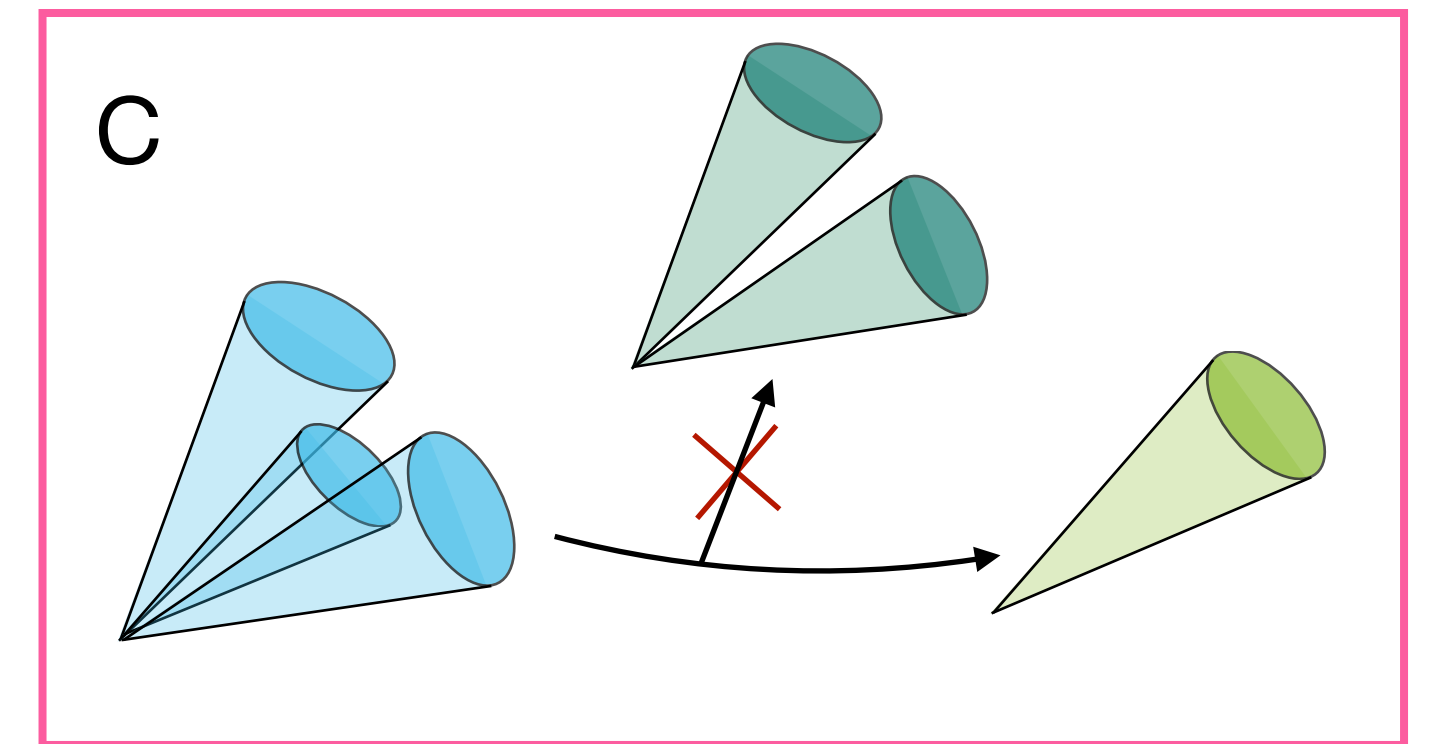
Two Interpretable Paths



Hierarchical ordering $t \rightarrow Z \rightarrow q/g$ reflects the successive loss of prongs.

Geometry VI

Two Interpretable Paths



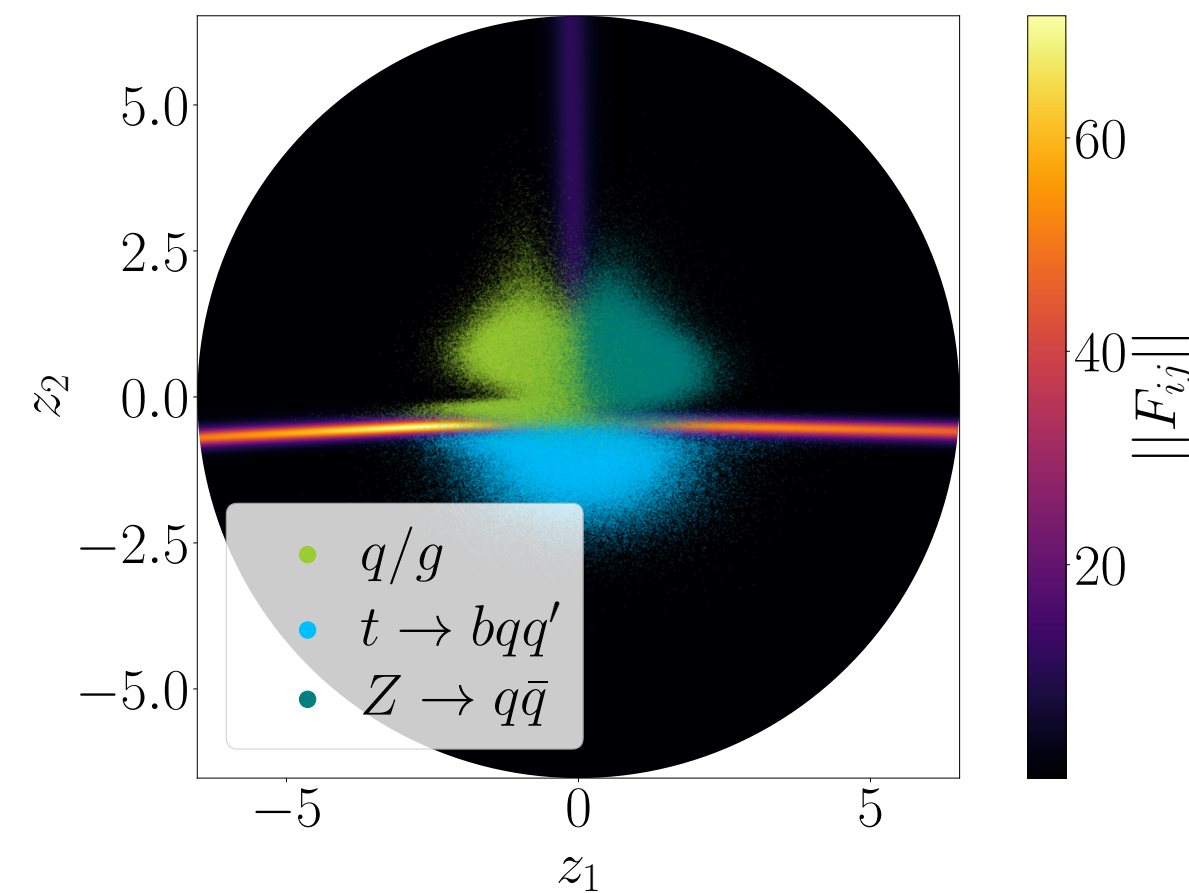
Hierarchical ordering $t \rightarrow Z \rightarrow q/g$ reflects the successive loss of prongs.

Conversely, $Z \leftrightarrow q/g$ is largely uninfluenced by t -jets.

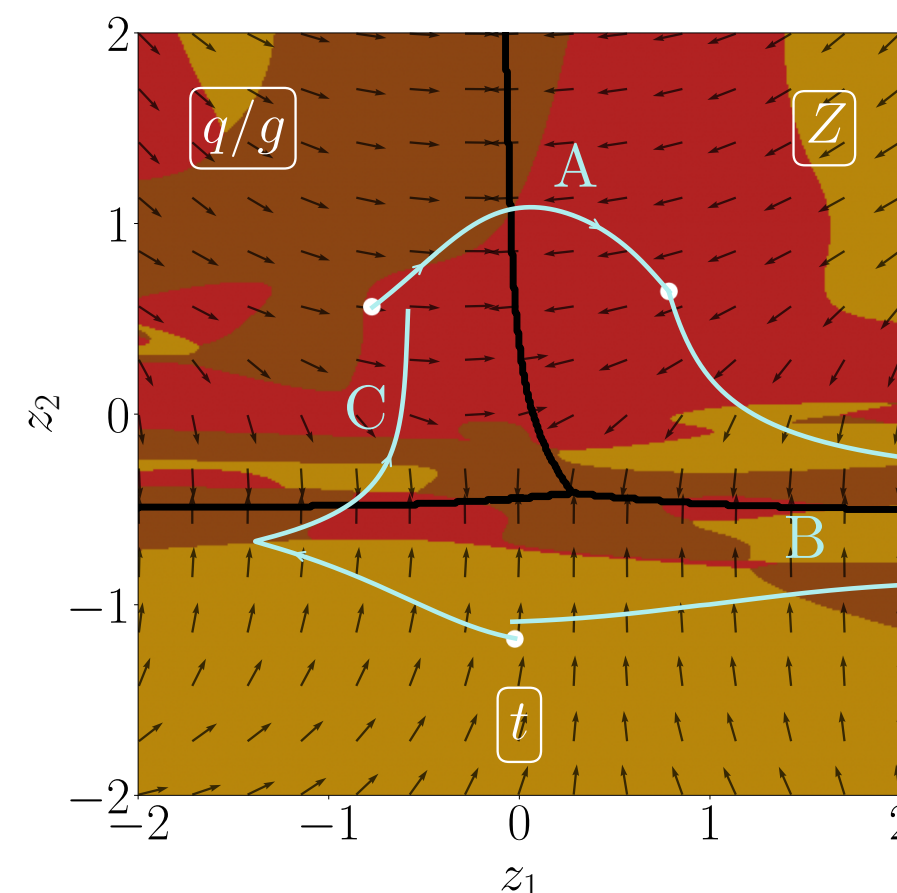
Take-Home

What can the geometry tell us?

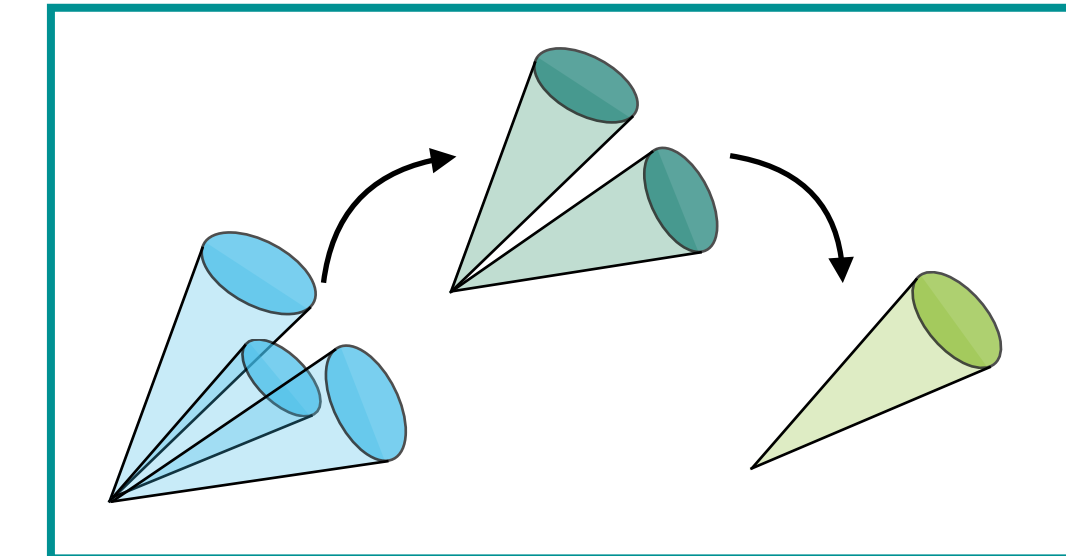
Thank you :)



...which regions and directions the classifier is sensitive to.



... which jet features are aligned with the discriminative classifier directions.



...which ordering and hierarchies appear in the jet observables.

References

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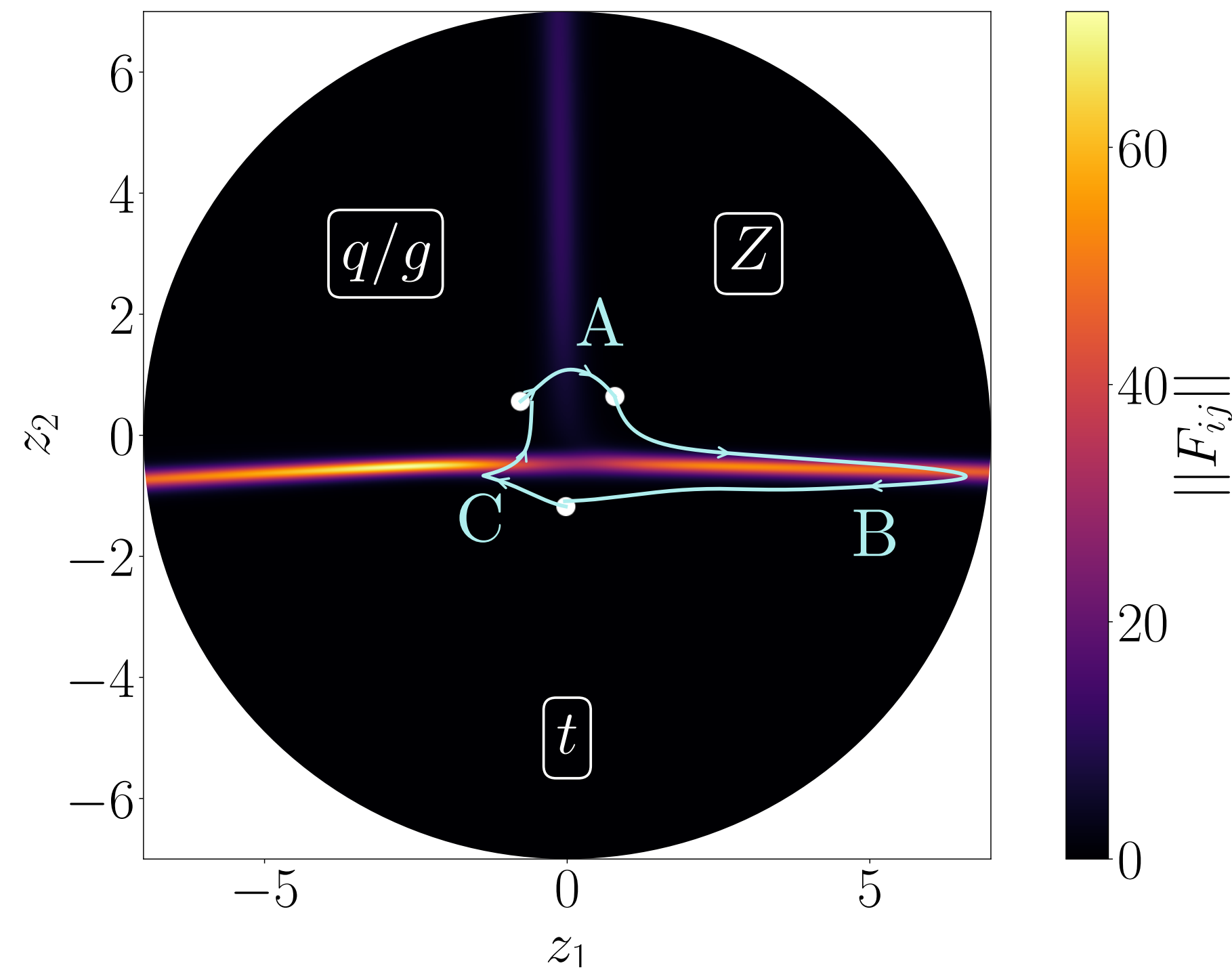
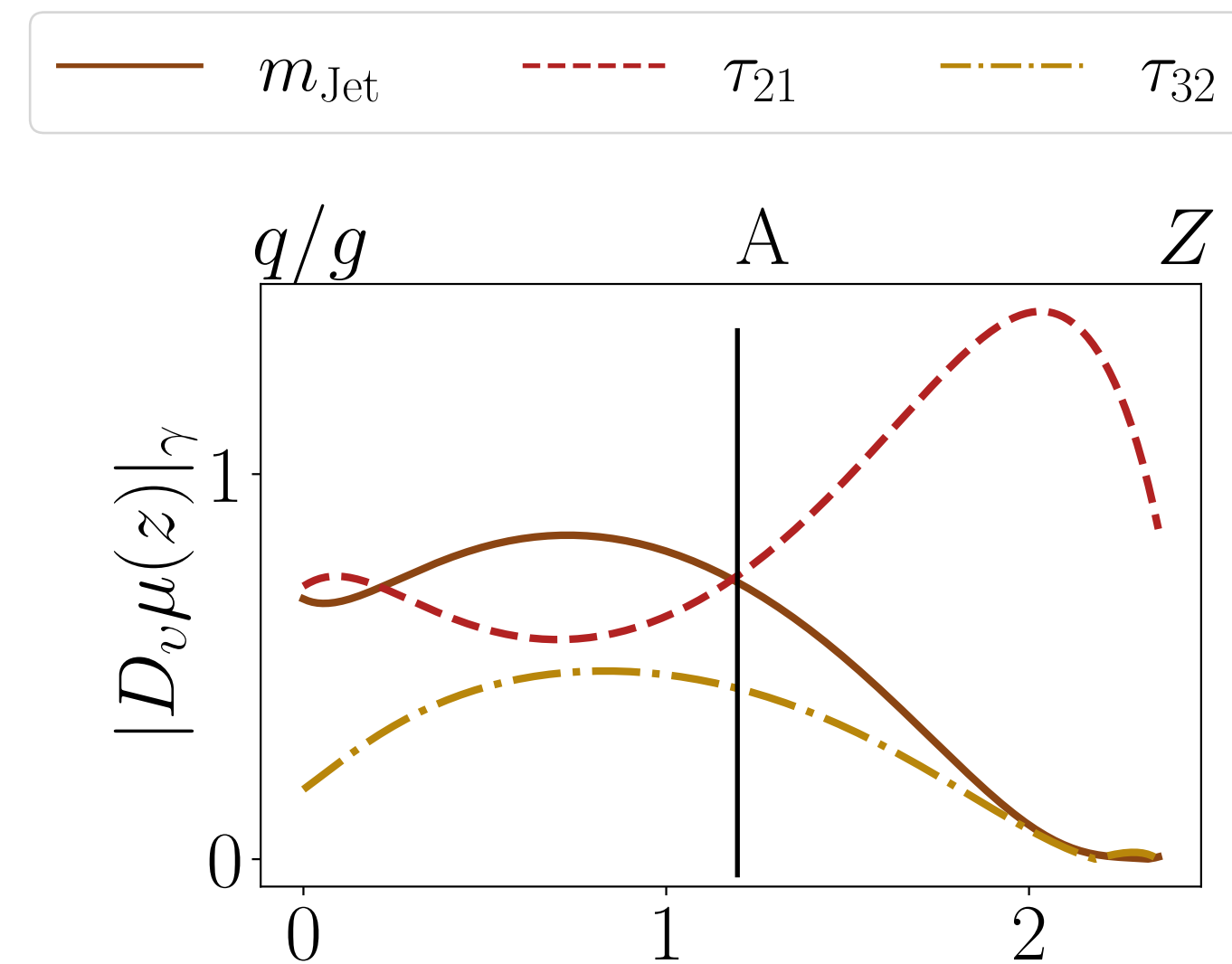
Butter, Dillon, Plehn, Vogel, “Performance versus resilience in modern quark-gluon tagging.” SciPost Phys. Core 6, 85 (2023)

Two geometries IV

Link Classifier Geodesics to Features

Classifier geodesic = quickest way to morph one event into another acc. to the classifier

Moving along this path, which physics feature μ dominates?



↪ First, m_{jet} dominates, the event is pushed to the Z -mass region.

↪ Then, the two-prong structure emerges, τ_{21} dominates.