

Information Geometry of Latent Representations for Interpretable Jet Tagging

Part II: What does geometry tell us about jets?

ML4Jets Vienna 2026 [[2603.02310](#)]

Benedikt Schosser | Institute for Theoretical Physics, Heidelberg University

Rebecca Maria Kuntz, Tilman Plehn, Björn Malte Schäfer, Sophia Vent

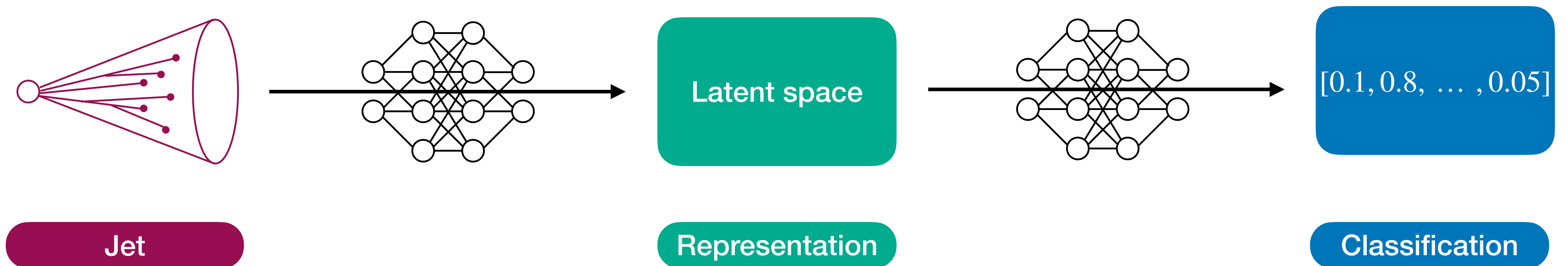


UNIVERSITÄT
HEIDELBERG
ZUKUNFT
SEIT 1386

Why understand a jet tagger?

Modern jet tagging:

Powerful classification from a learned high-dimensional representation



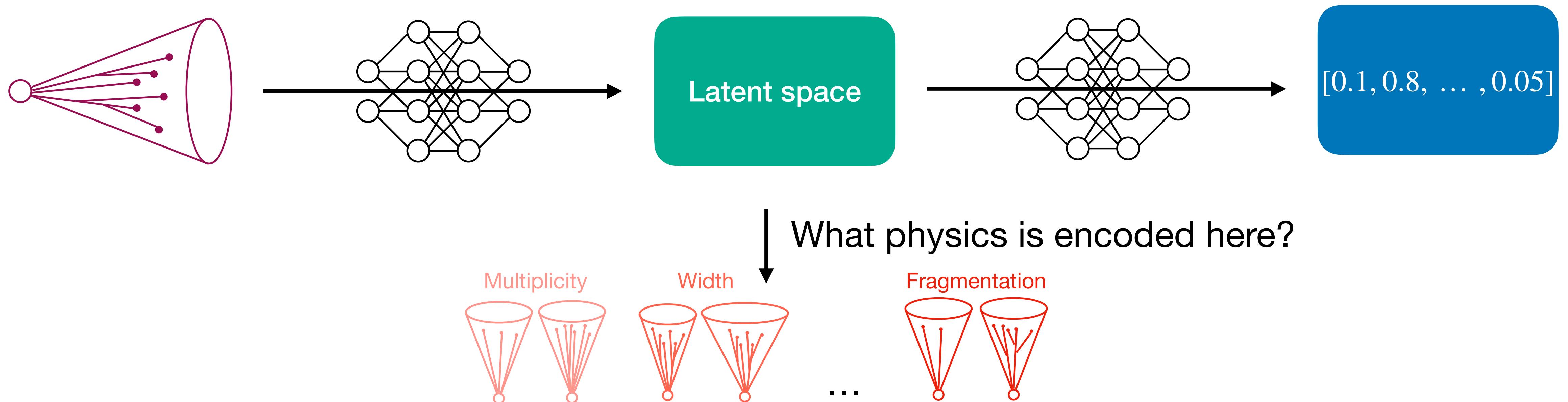
Why understand a jet tagger?

Modern jet tagging:

Powerful classification from a learned high-dimensional representation

Physical questions:

- Which physical features does the classifier use?
- Where in the latent space do they matter?
- How does the classifier move between physical jet configurations?



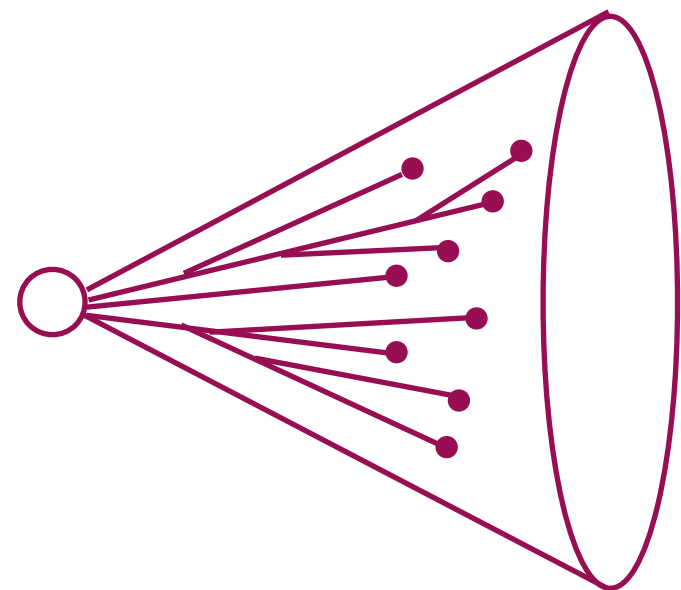
Quark-gluon tagging

Quark-gluon tagging

Physics expectation:

Gluon jet

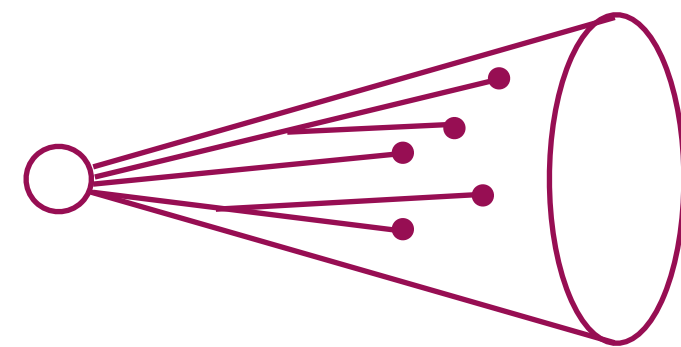
- More particles
- Wider
- Softer fragmentation



$$C_A > C_F$$

Quark jet

- Fewer particles
- Narrower
- Harder fragmentation

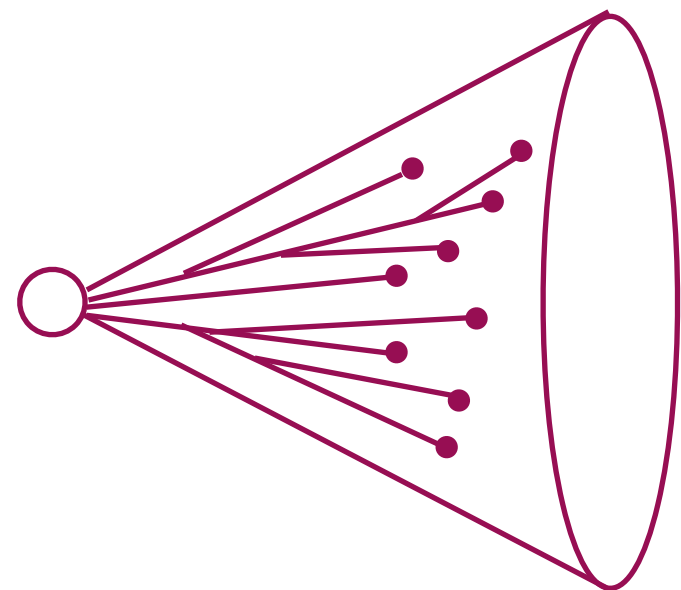


Quark-gluon tagging

Physics expectation:

Gluon jet

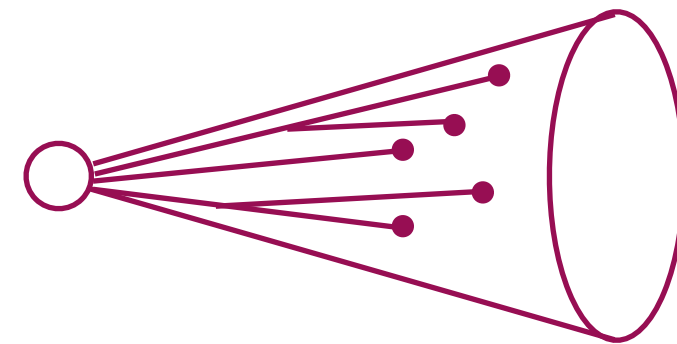
- More particles
- Wider
- Softer fragmentation



$$C_A > C_F$$

Quark jet

- Fewer particles
- Narrower
- Harder fragmentation

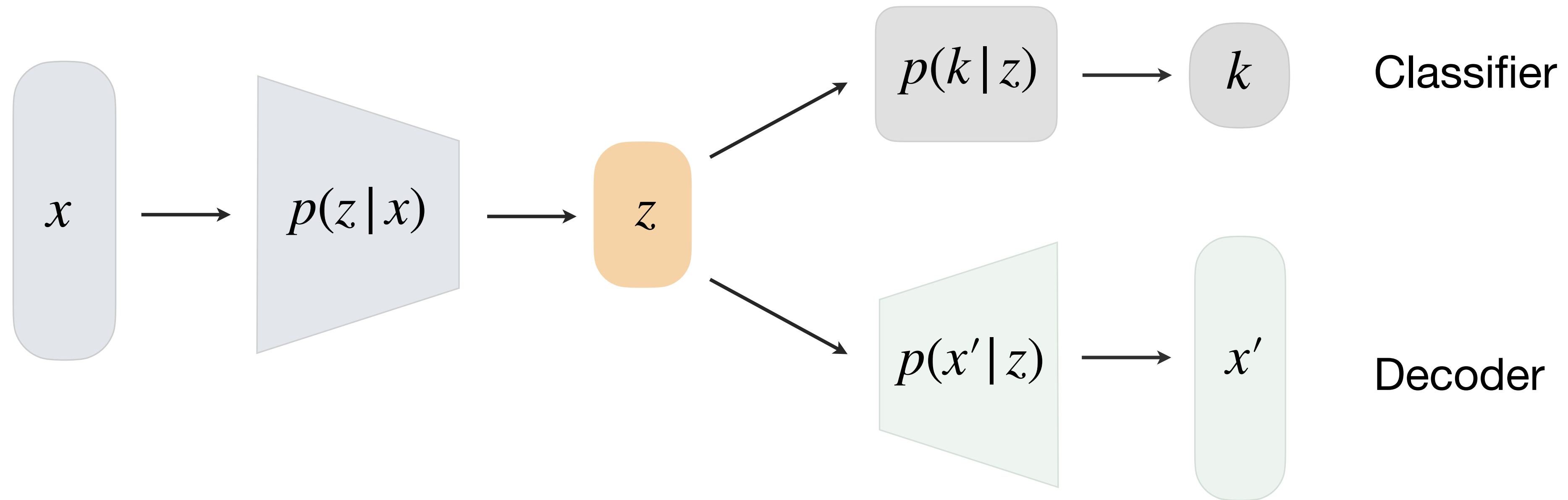


However ...

- q/g labels are not unambiguous beyond leading order
- Discrimination is sensitive to showering and hadronization

Does the learned representation organize itself according to this expected QCD structure?

Setup — variational autoencoder

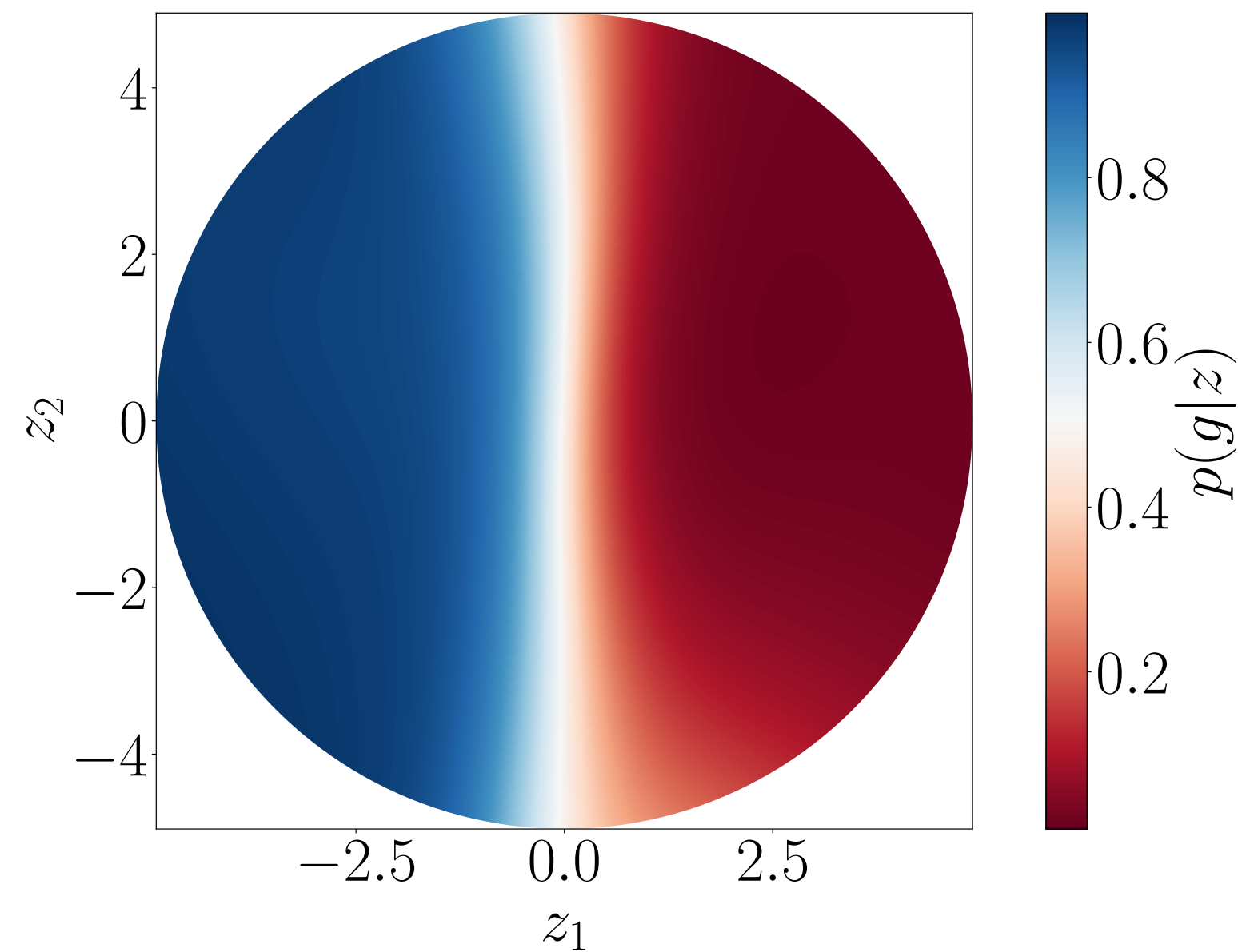


Latent space $z \sim \mathcal{N}(\mu, \sigma)$

Reconstructed features: $\{n_{\text{PF}}, w_{\text{PF}}, p_T D, C_{0.2}, \epsilon, m_{\text{Jet}}, x_{\text{max}}, S_{\text{frag}}\}$

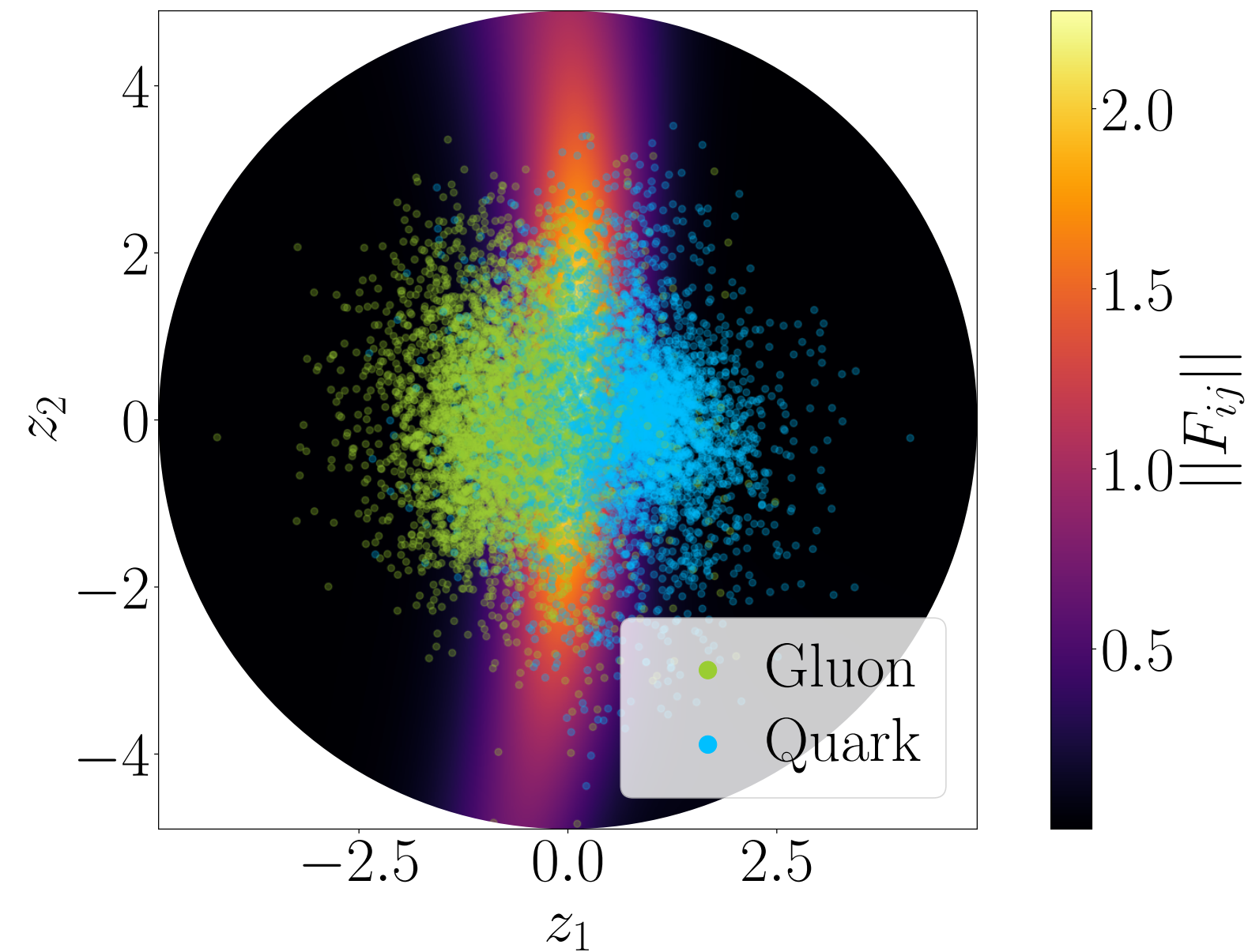
Classifier metric

Decision boundary



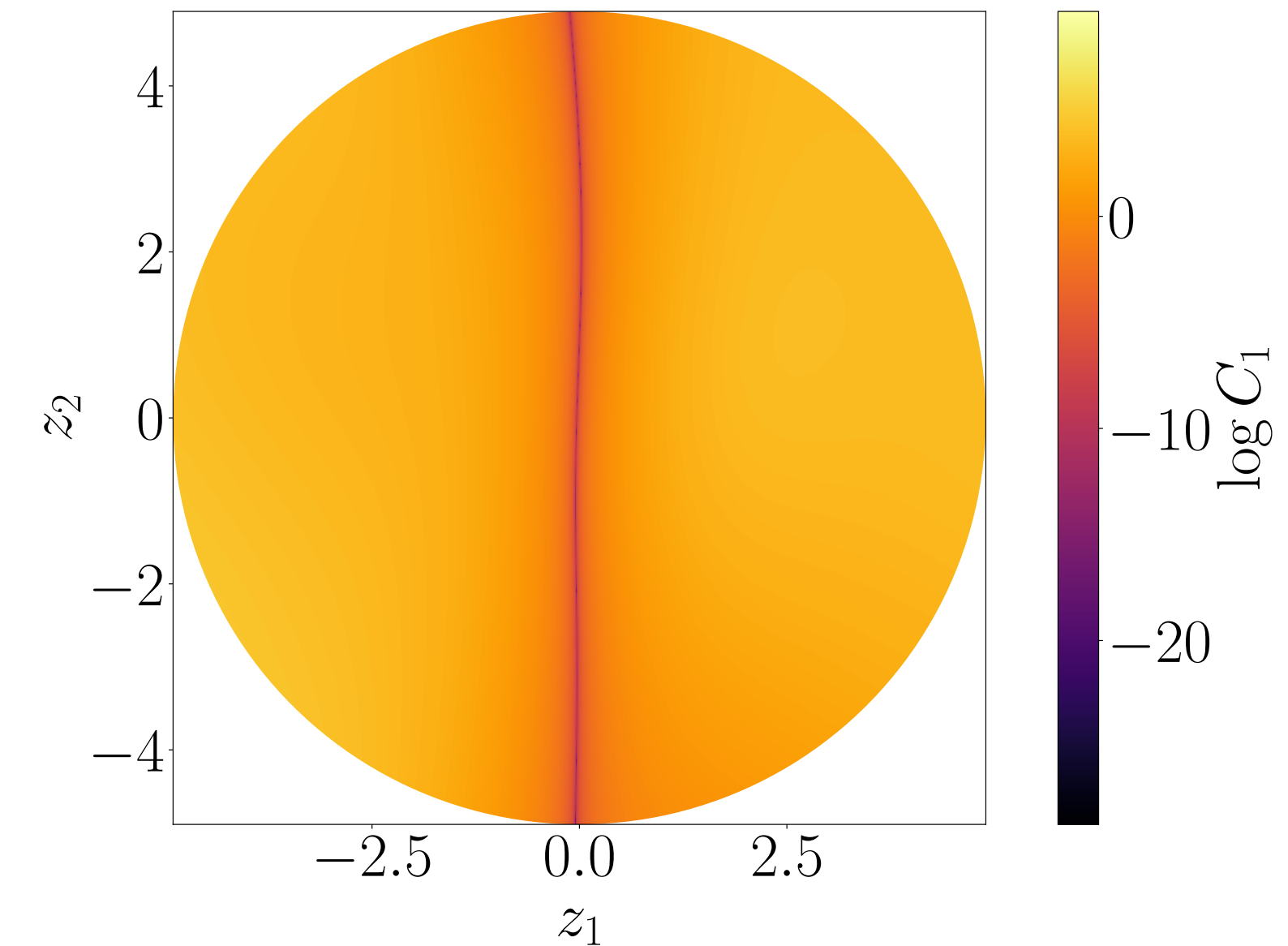
$$p = \frac{1}{2}$$

Fisher metric



Network sensitivity

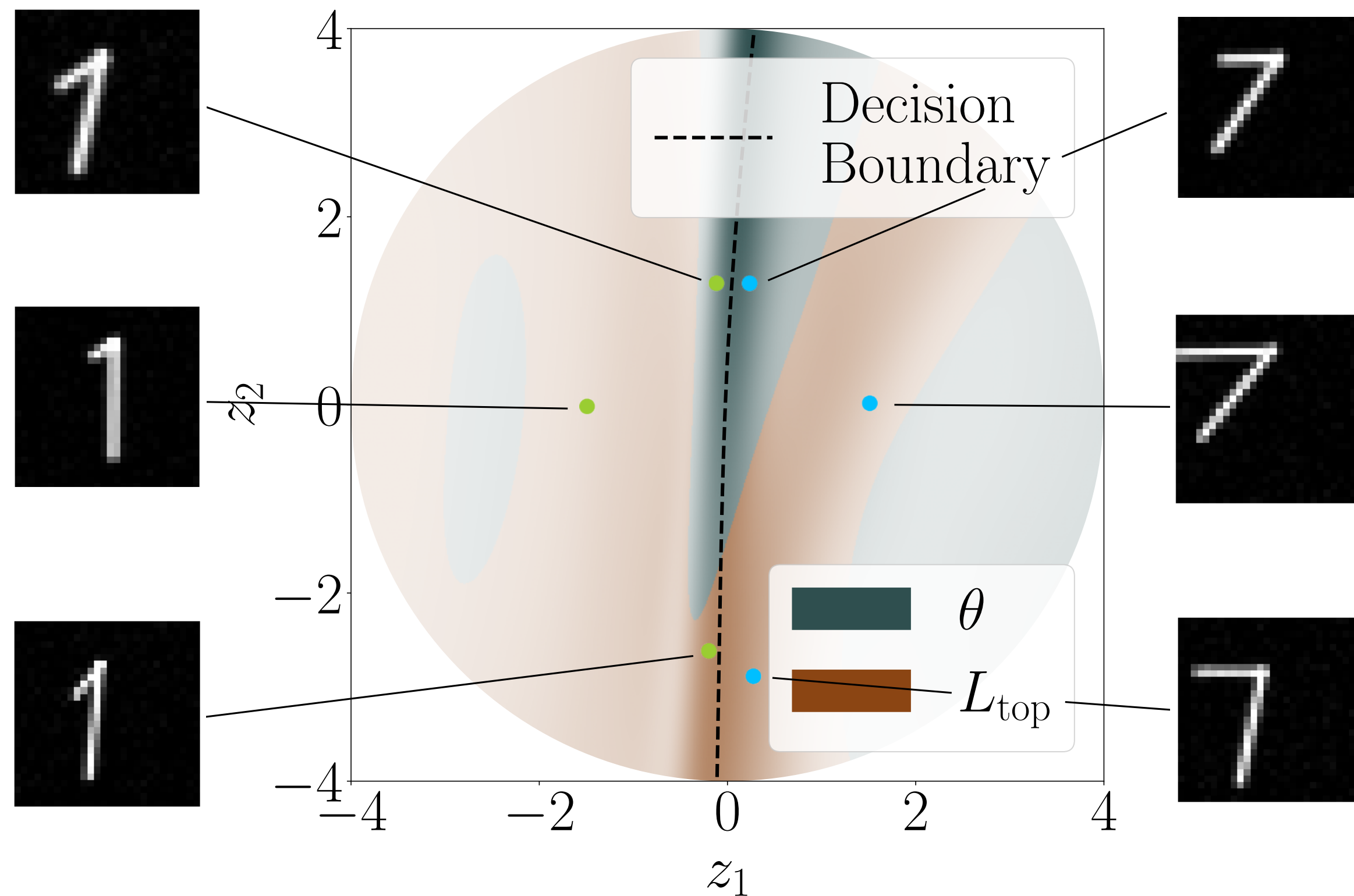
Fully contracted ACT



Likelihood skewness

Which features change with the decision?

Reminder MNIST

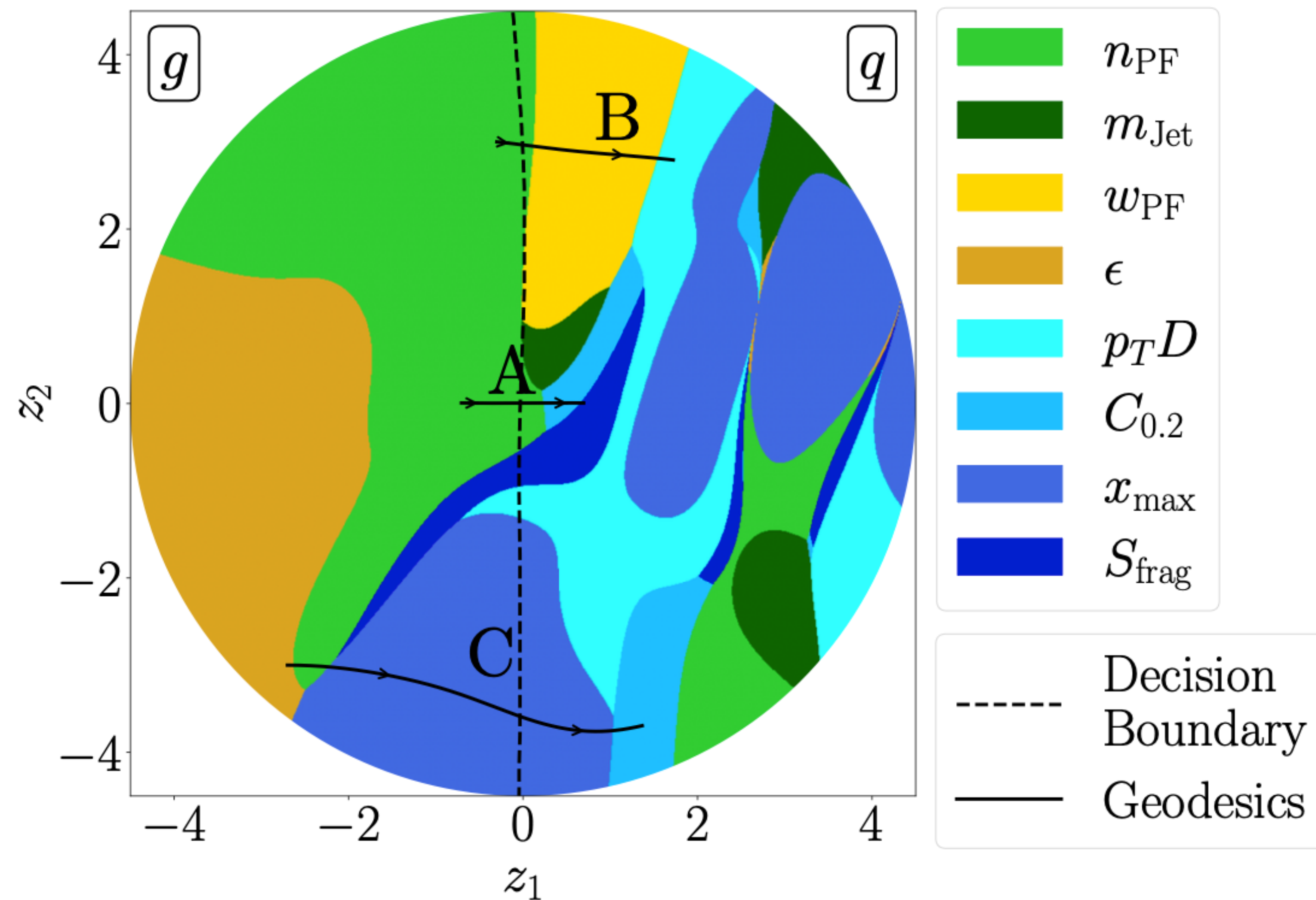


Fisher directional derivative:

How do the reconstructed features change in the most sensitive direction of the classifier?

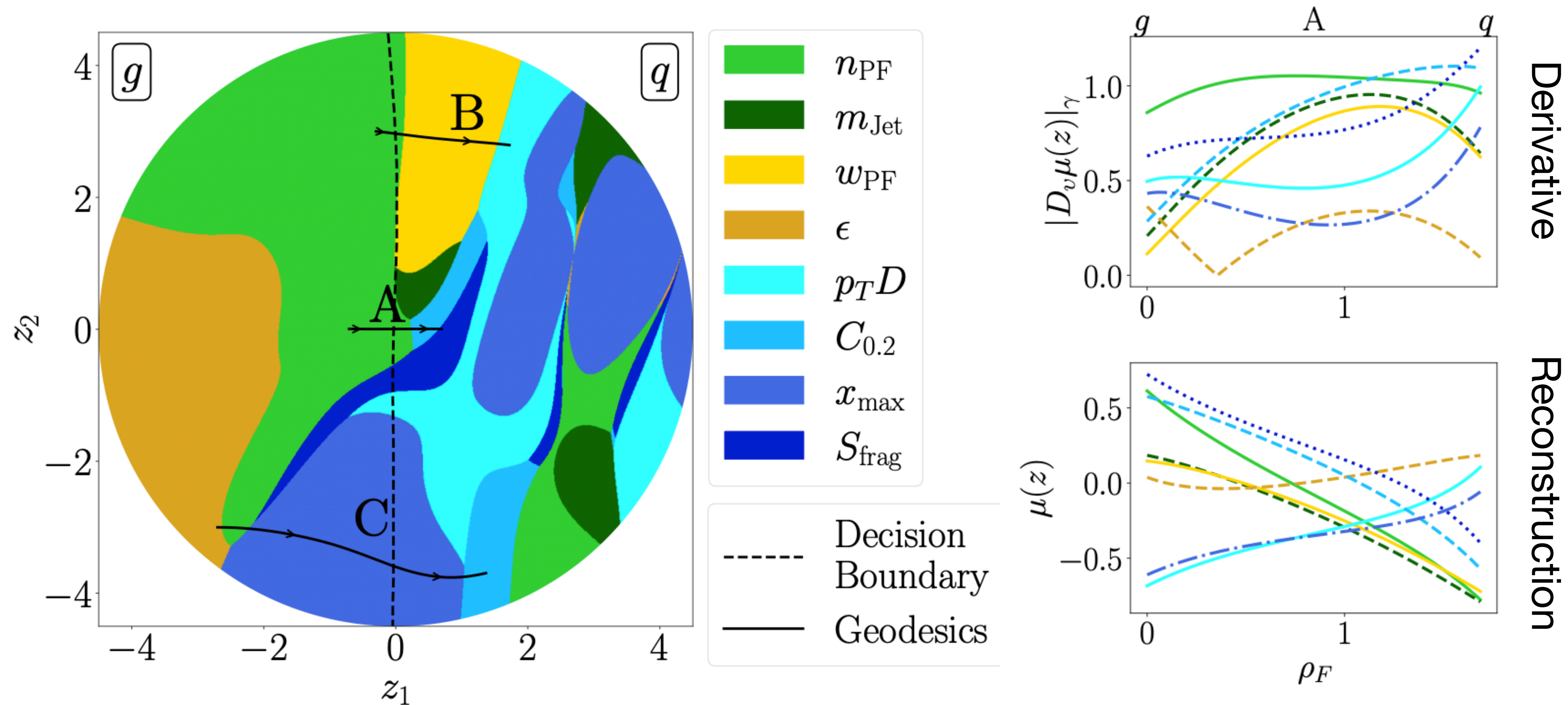
“Which feature is best aligned with the decision”

Which features change with the decision?



- Gluon-like region: dominated by multiplicity
- Quark-like region: more heterogeneous
- The latent space separates into regions governed by **multiplicity**, **fragmentation** & **radiation shape**

Which features change with the decision?

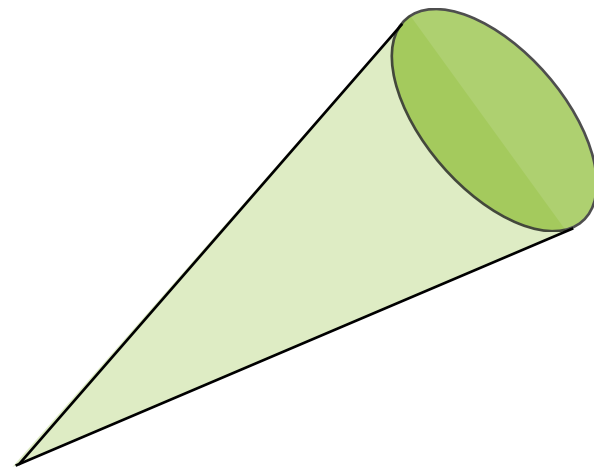


Along a classifier geodesic, we can track how the physics changes

Binary → multiclass

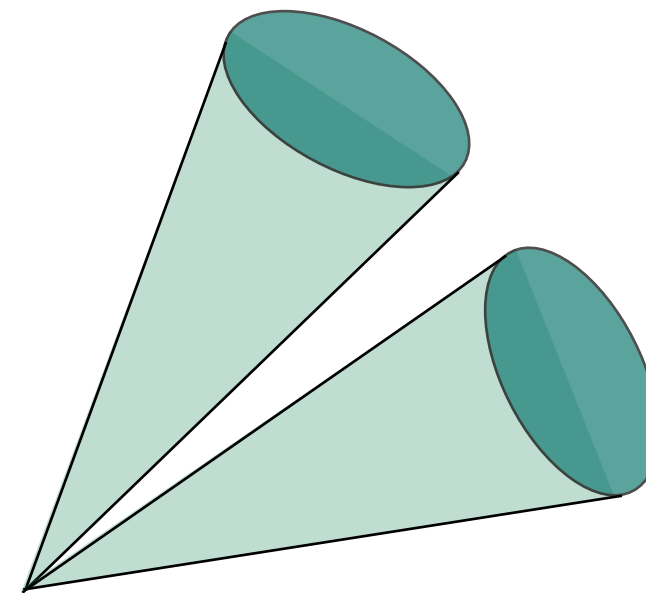
Three-fold jet tagging

q/g



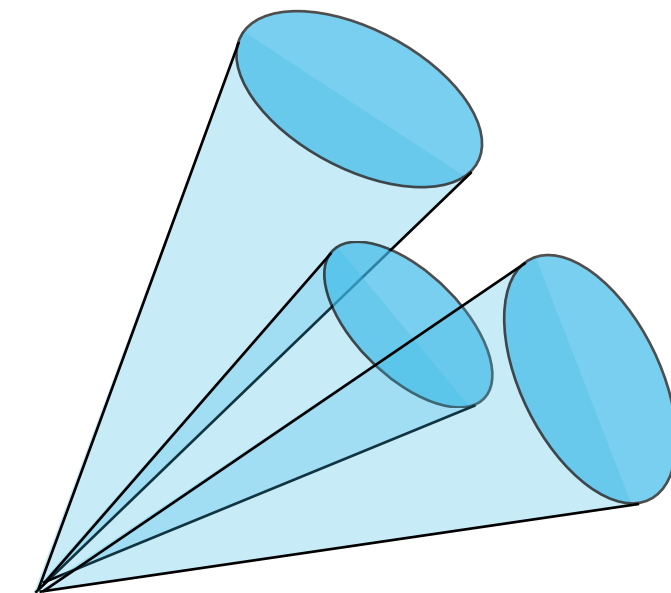
1-prong

$Z \rightarrow q\bar{q}$



2-prong

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



3-prong

Features:

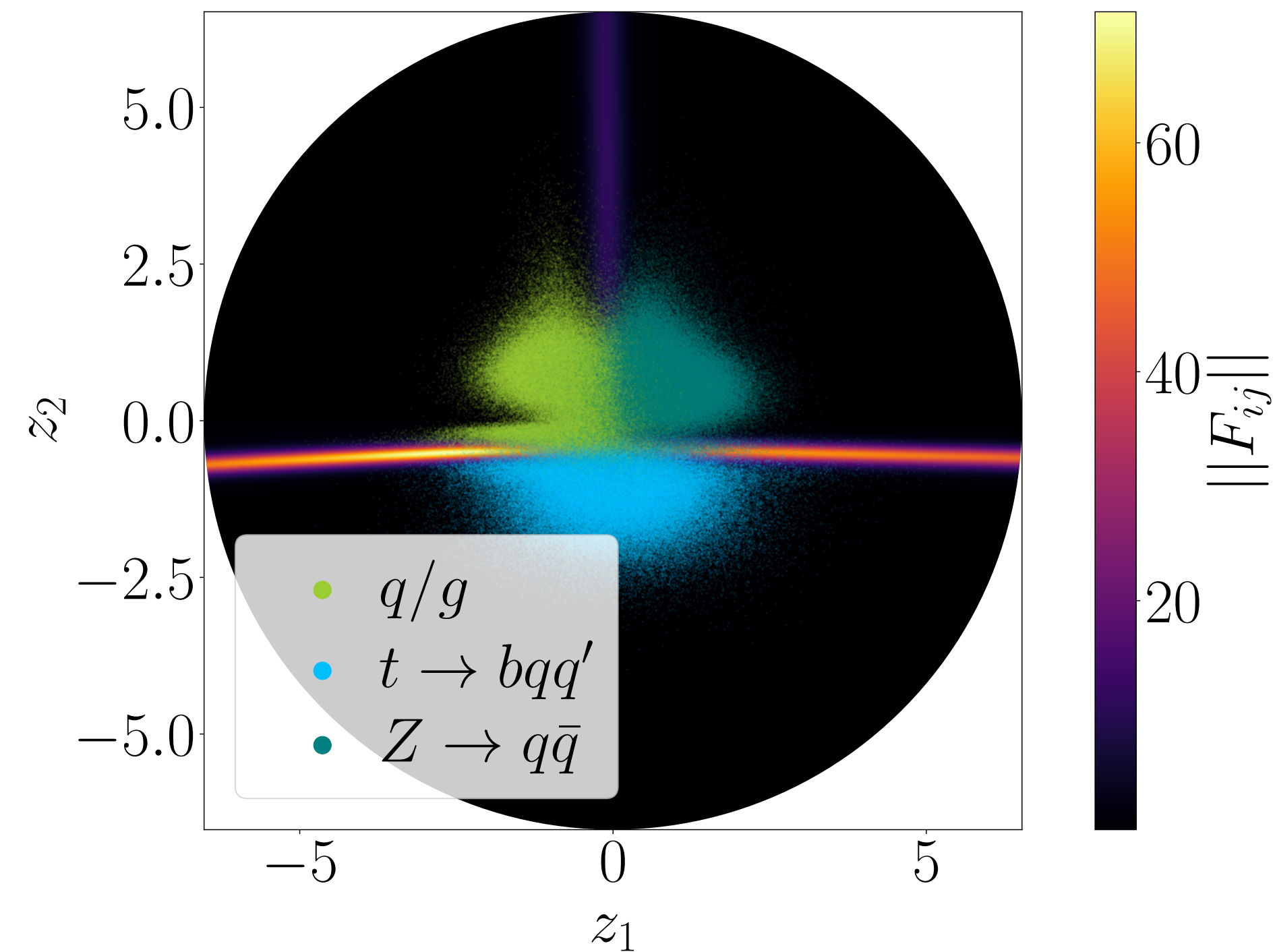
m_{Jet}

$\tau_{21} : 1 \leftrightarrow 2 \text{ - prong}$

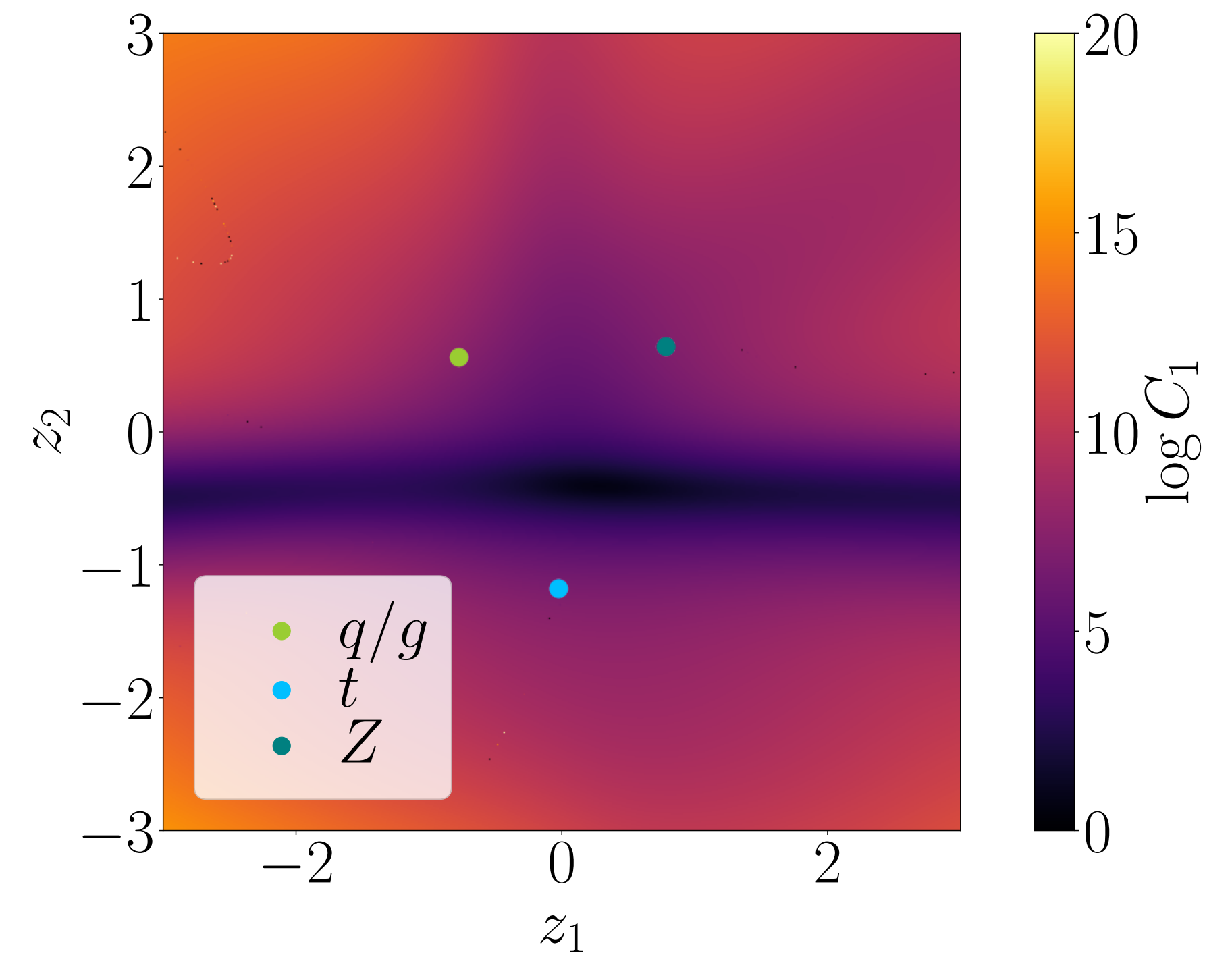
$\tau_{32} : 3 \leftrightarrow 2 \text{ - prong}$

Classifier metric

Fisher metric

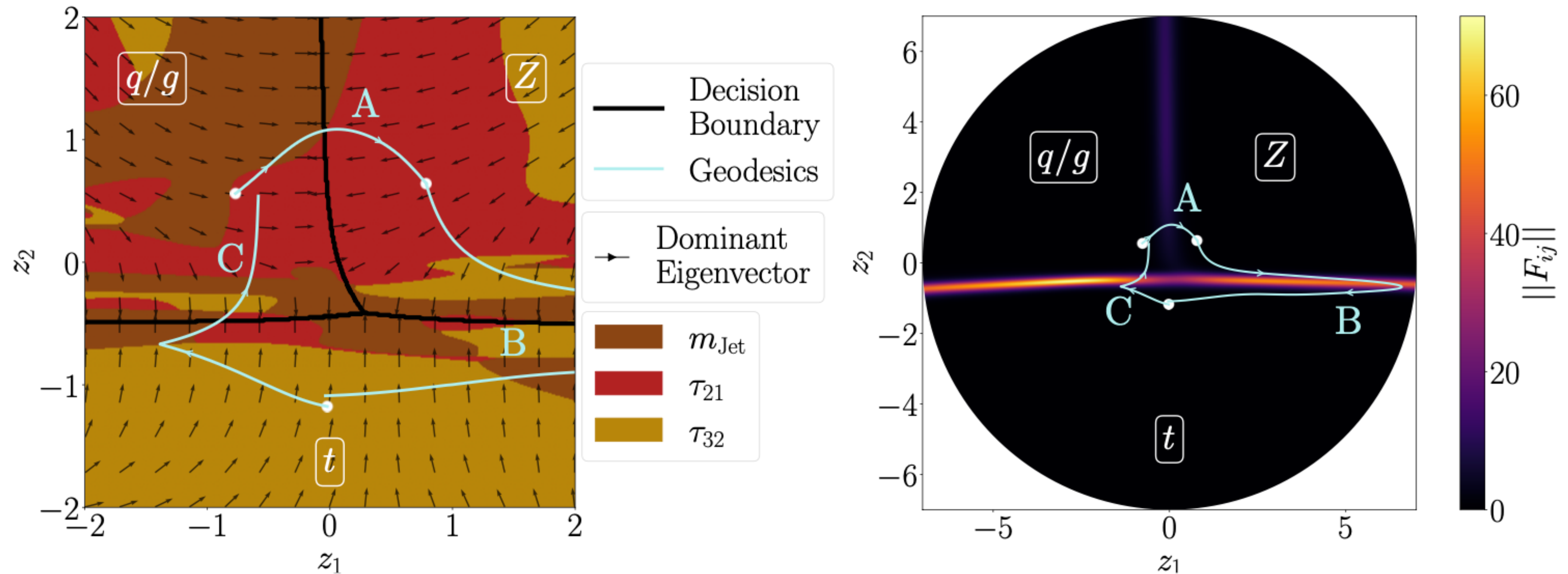


Fully contracted ACT



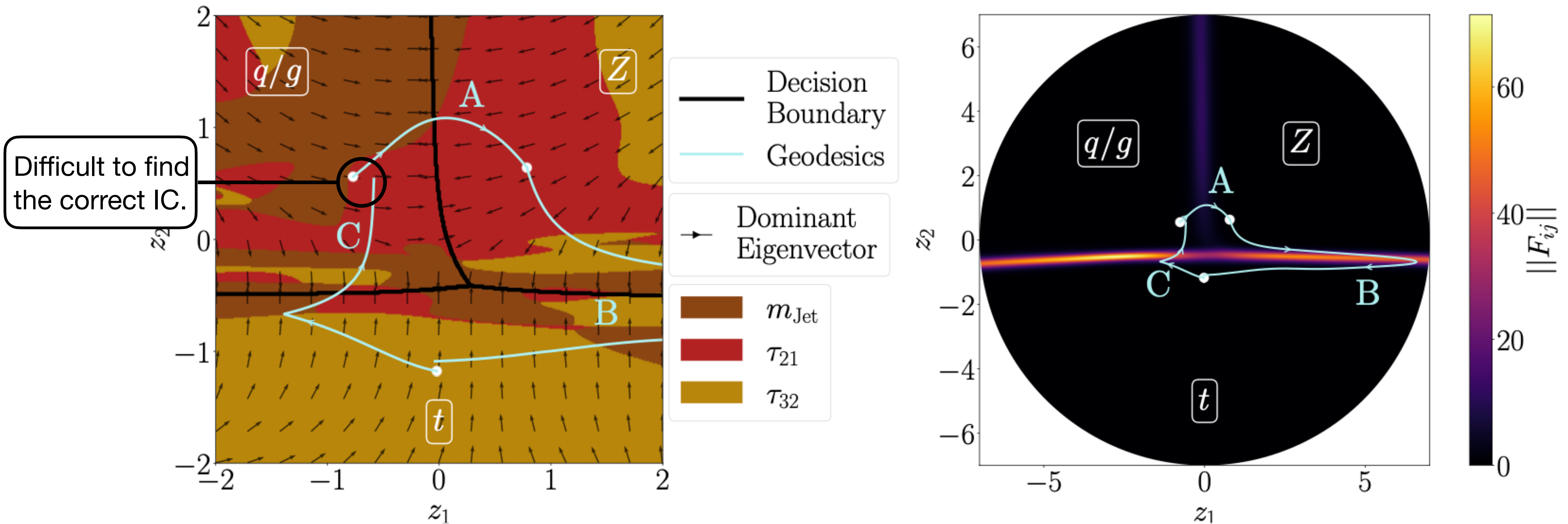
Top jets form a distinct region, while q/g and Z remain more closely connected

Dominant features & geodesics



- Substructure observables dominate most of the latent space
- Jet mass becomes important near class boundaries
- The natural $Z \rightarrow \text{top}$ path avoids the q/g region

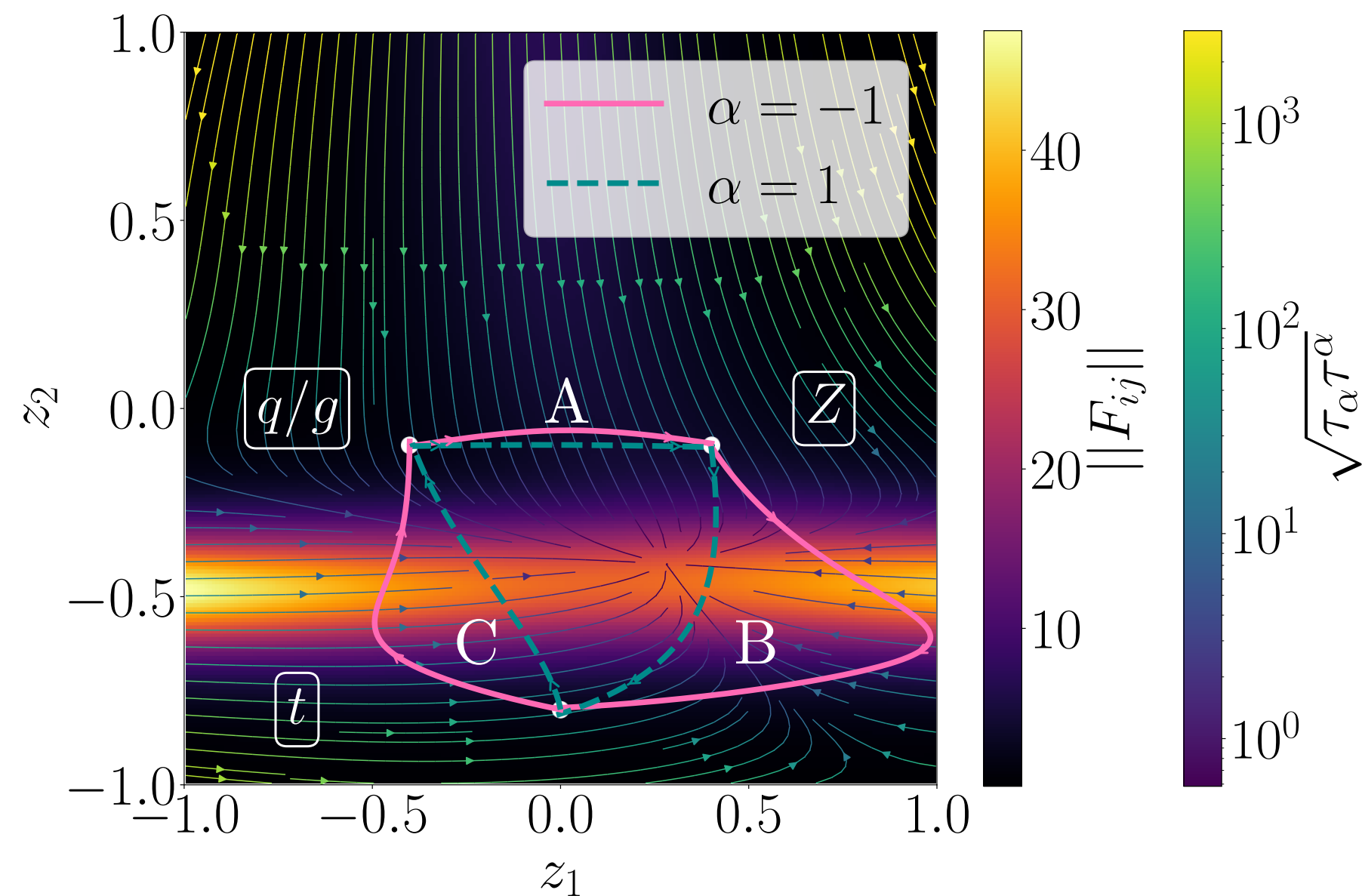
Dominant features & geodesics



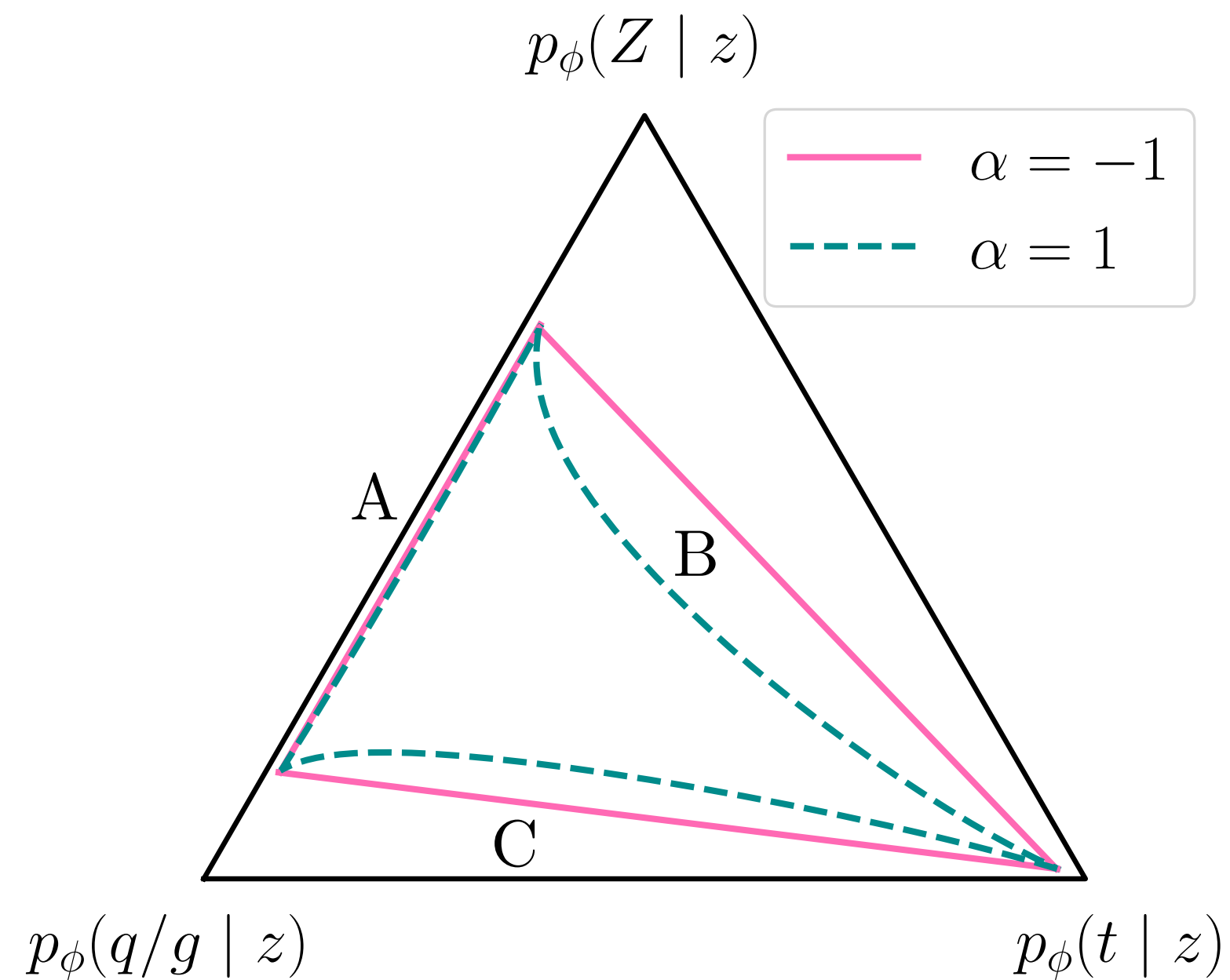
- Substructure observables dominate most of the latent space
- Jet mass becomes important near class boundaries
- The natural $Z \rightarrow$ top path avoids the q/g region

Dual structure

Learned latent space



Simplex



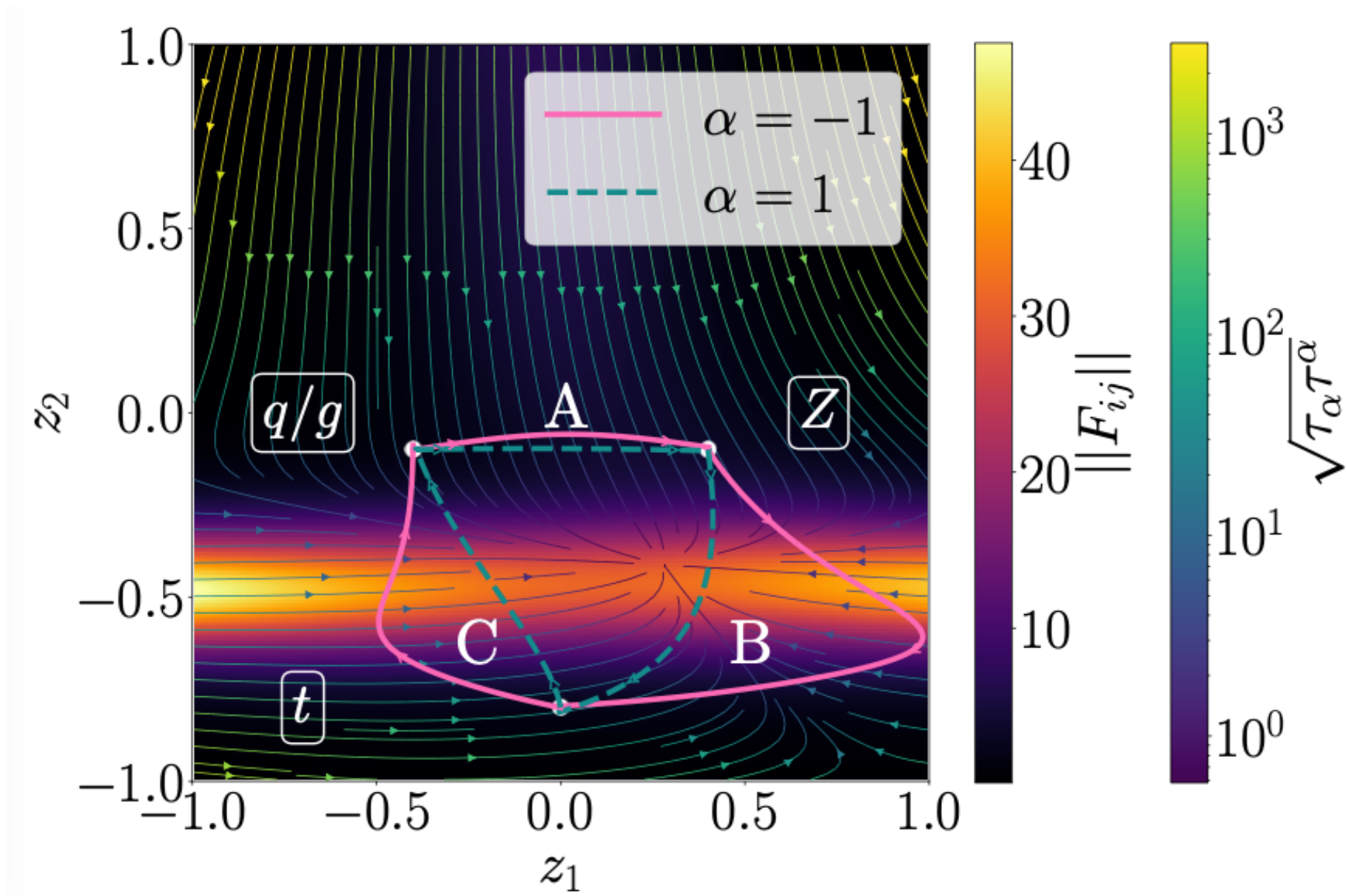
Connections Γ derived from

- Forward KL: $\alpha = -1$
- Backward KL: $\alpha = +1$

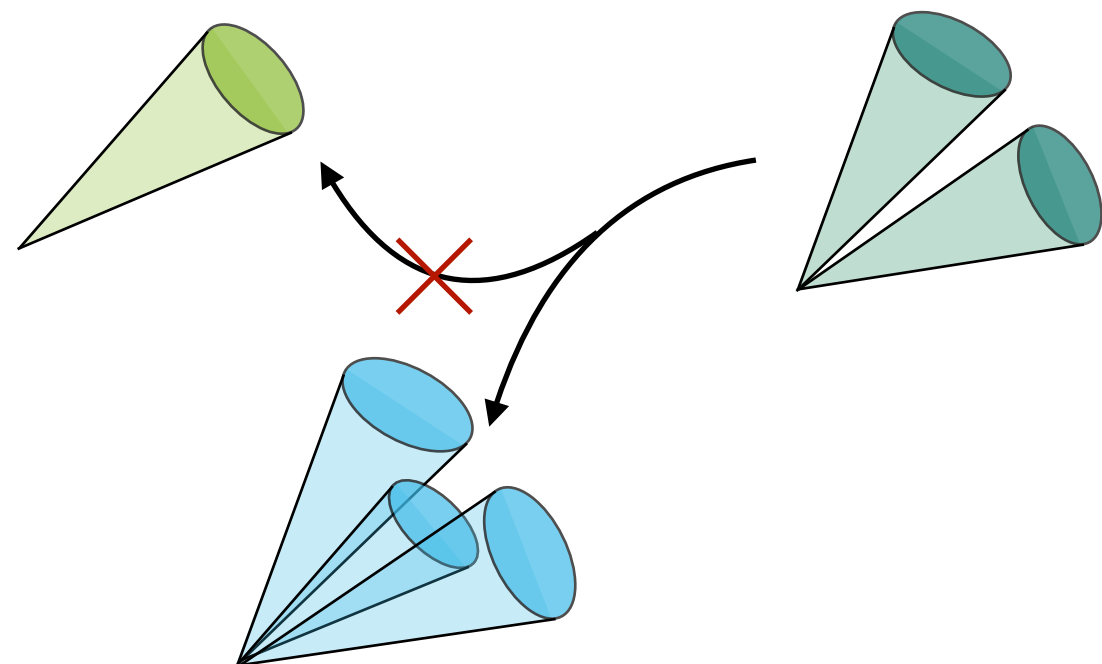
- Same endpoints, different natural paths
- The difference is largest when the third class becomes relevant

Dual structure

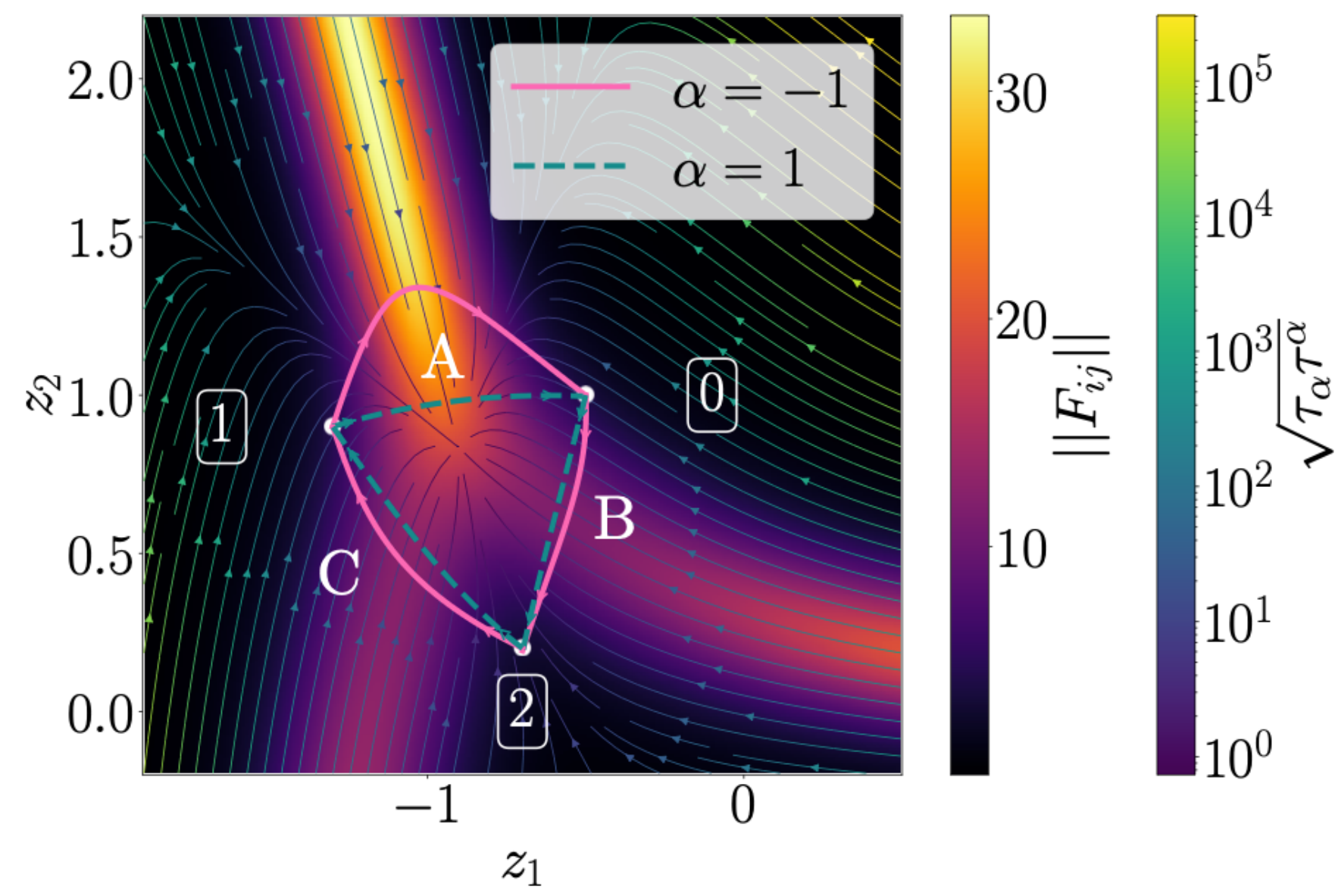
Jets



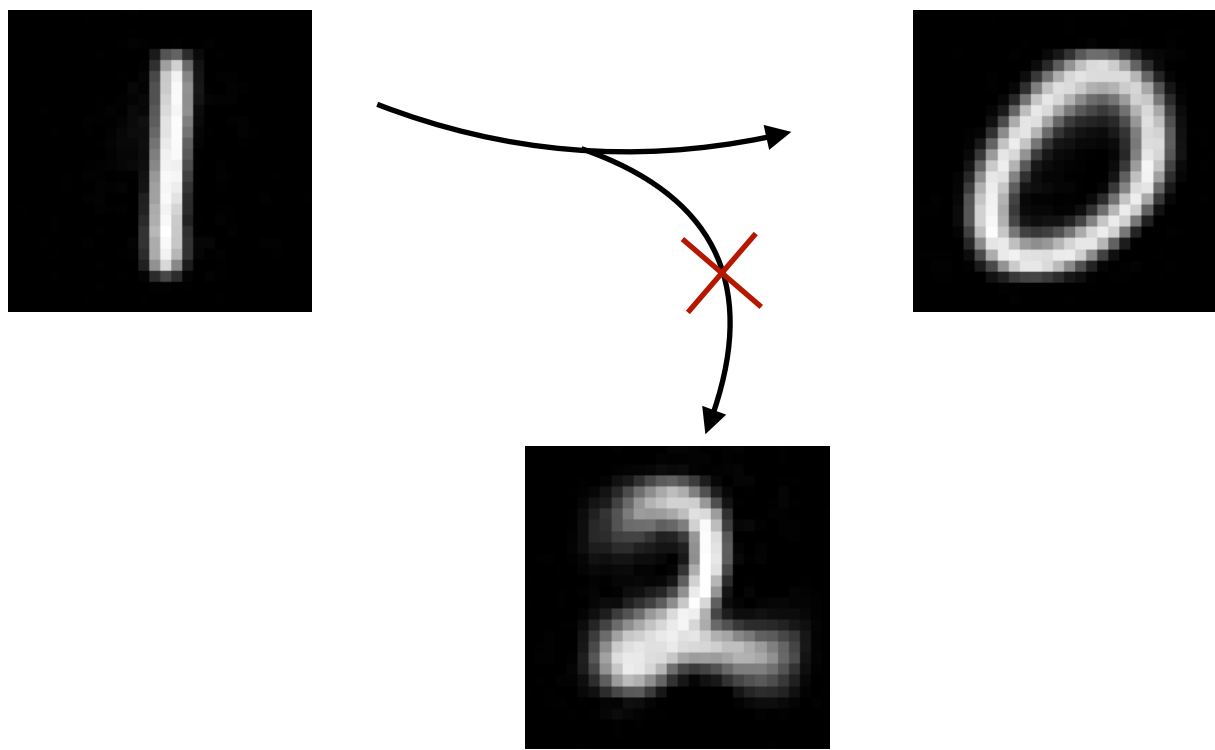
- The $Z \rightarrow$ top path is shaped by the q/g region



MNIST



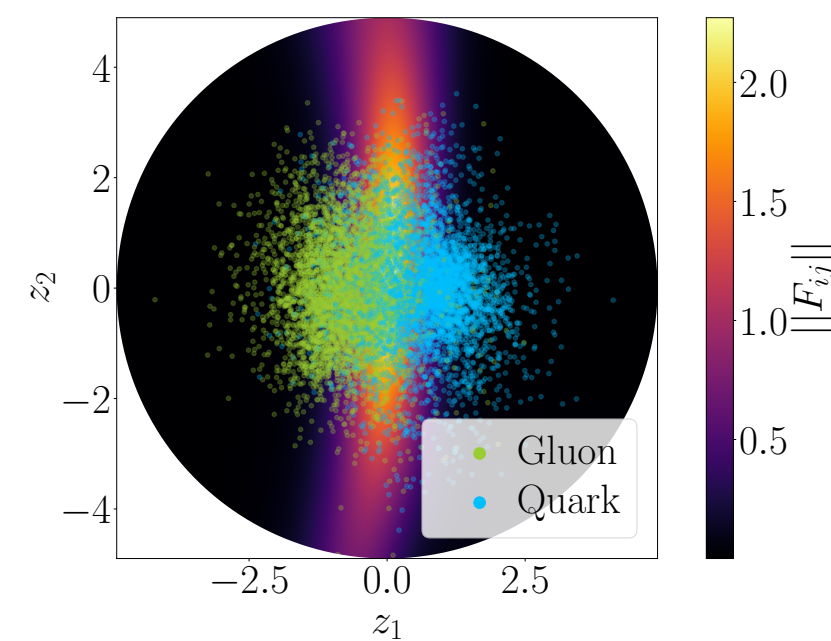
- The $1 \rightarrow 0$ path is shaped by the 2 region



Information gained through geometry

Where?

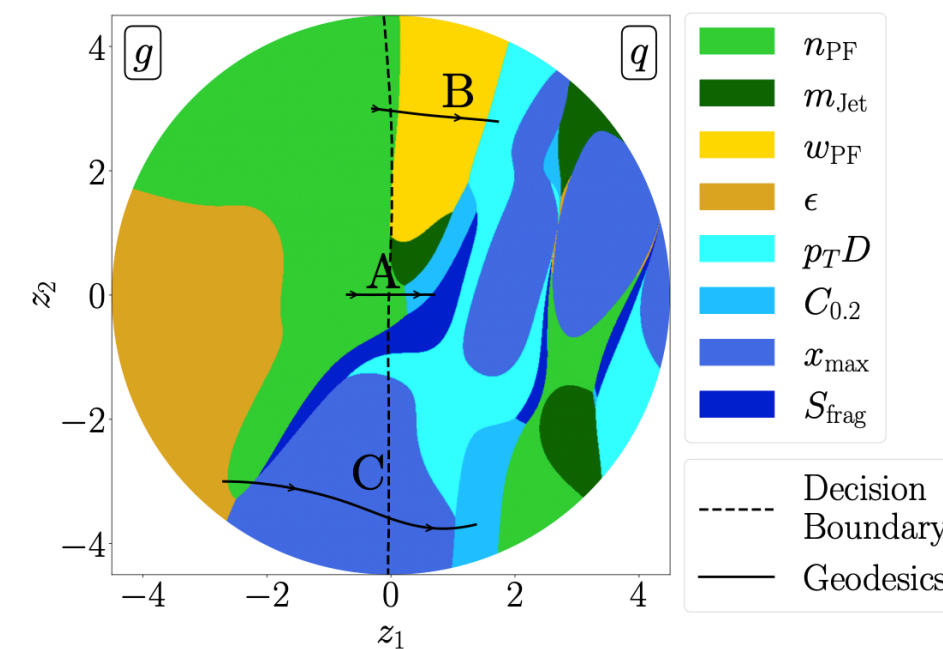
Classifier geometry



Identifies classifier-sensitive regions and directions

What?

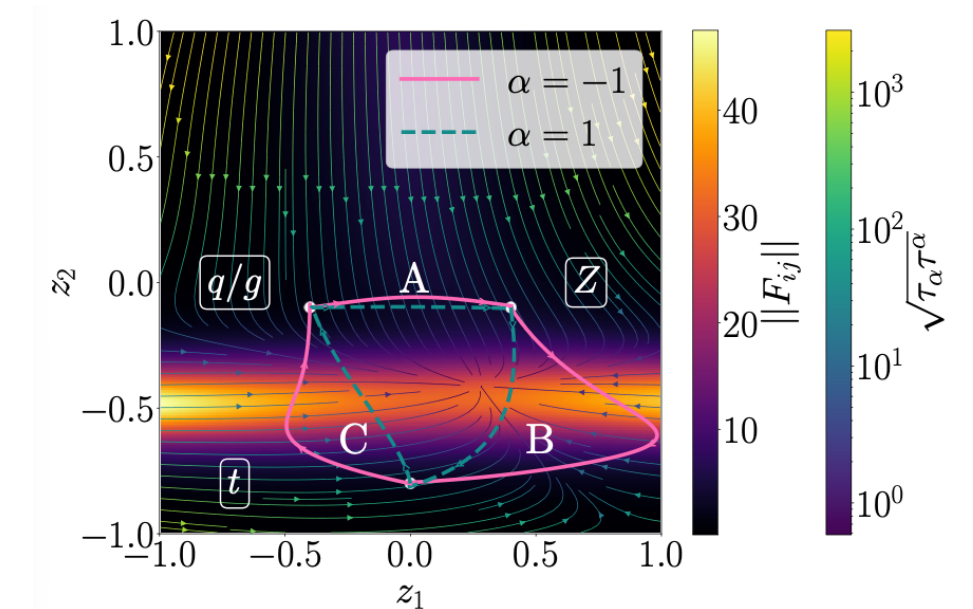
Feature-decision alignment



Connects classifier-relevant directions to physical jet features

How?

Geodesics



Reveals physically interpretable paths between classes