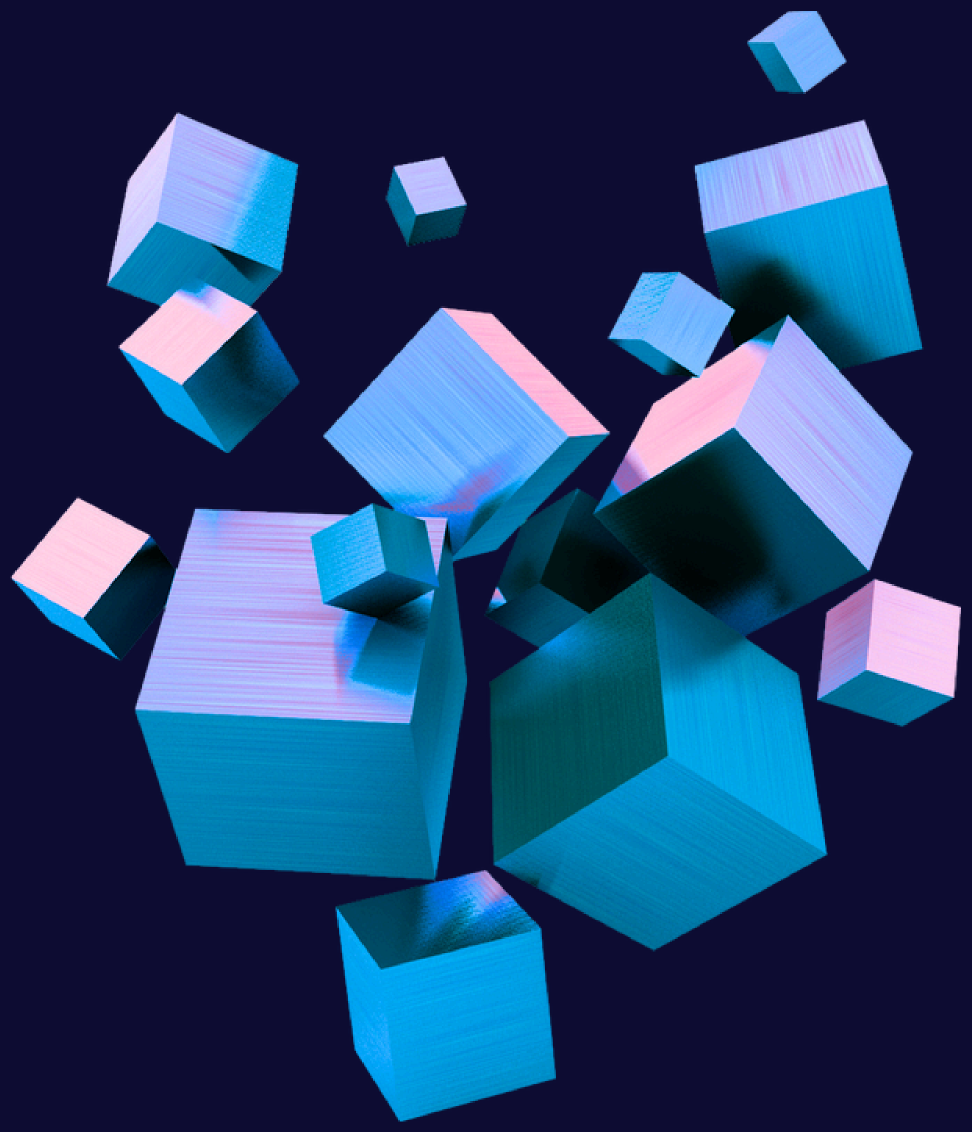


# 3rd Week
# The Bridge

**Clusters**
**01/22 - 01/26**

Josefa Fernández

# ToDo

- Repeat the same in FRGC database
- VPN

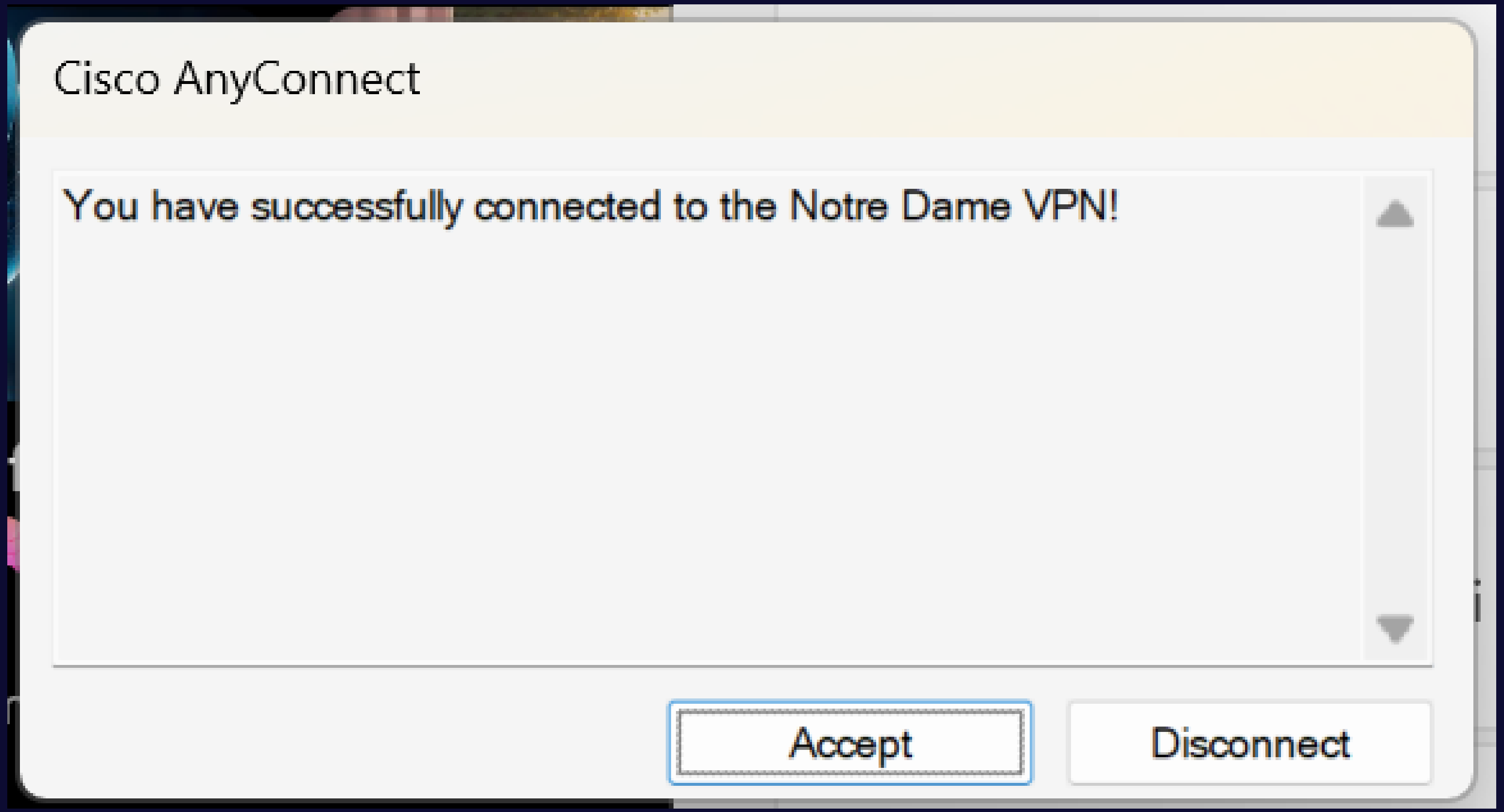
# Thursday

22th January

# VPN

- Install and connected VPN
- Connected to eduroam
- But still dont connect cvrl-flynn-ws1

https://esc.nd.edu/support/vpn/

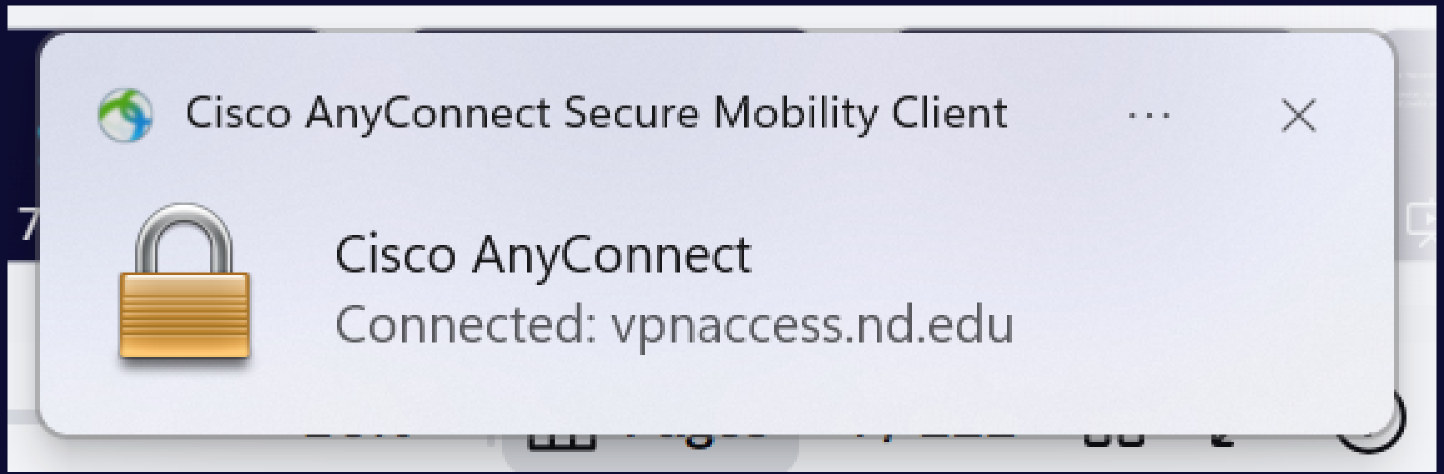


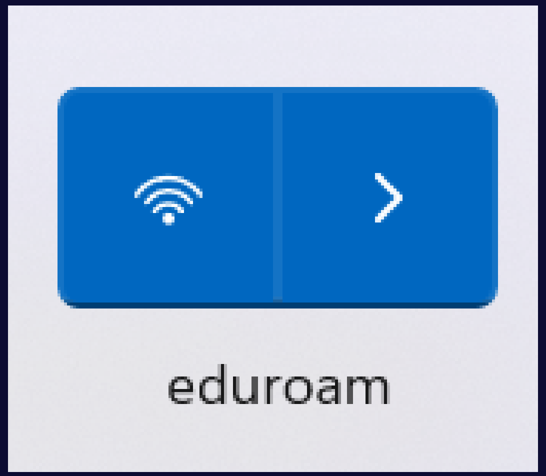

```
C:\Users\Usuario>ping vpnaccess.nd.edu

Haciendo ping a vpnaccess.nd.edu [129.74.249.147] con 32 bytes de datos:
Respuesta desde 129.74.249.147: bytes=32 tiempo=4ms TTL=251
Respuesta desde 129.74.249.147: bytes=32 tiempo=8ms TTL=251
Respuesta desde 129.74.249.147: bytes=32 tiempo=5ms TTL=251
Respuesta desde 129.74.249.147: bytes=32 tiempo=6ms TTL=251

Estadísticas de ping para 129.74.249.147:
    Paquetes: enviados = 4, recibidos = 4, perdidos = 0
    (0% perdidos),
Tiempos aproximados de ida y vuelta en milisegundos:
    Mínimo = 4ms, Máximo = 8ms, Media = 5ms

C:\Users\Usuario>ssh jferna27@cvrl-flynn-ws1
ssh: connect to host cvrl-flynn-ws1 port 22: Connection timed out
```



# Setup to FRGC dataset

```
import os
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.metrics.pairwise import cosine_similarity
import cv2
from insightface.app import FaceAnalysis
from tqdm import tqdm
import pandas as pd
from joblib import Parallel, delayed
```

# Use FRGC dataset

- See the data
- 1st , 5 characters, are the ID person
- 2 options:
  - Directory scan d1/jferna27/FRGC-nd1/all
  - Csv saved with the enbeddings, label, image_file, person_id

```
Found frgc_face_embeddings.csv, person ids loaded from csv
Total images: 39327
Identities: 568
```

# Extract Embeddings

- Initialize Face Detection + Embeddings
  - ArcFace: face detection
  - RetinaFace: extract embedding
- Extract Embeddings with parallel processings on both GPUs (0,1) or use the saved csv
  - Parallel and delayed from joblib
  - os.environ[CUDA_VISIBLE_DEVICES] = ‘0,1’
  - It takes 2:30:00 to extract the embeddings
- Save csv for the 1st time

```
Found frgc_face_embeddings.csv
Embeddings: (39327, 512)
Valid images: 39327
Unique identities: 568
```

# Cluster by Identity

- Cluster by identity
- Cluster stats
  - centroid
  - radius
  - dispersion
  - number of imgs

```
cluster_stats = {}
for lbl, cluster in identity_clusters.items():
    centroid = cluster.mean(axis=0)
    distances = np.linalg.norm(cluster - centroid, axis=1)
    cluster_stats[label_names[lbl]] = {
        "centroid": centroid,
        "radius": distances.max(),
        "dispersion": distances.std(),
        "num_images": len(cluster)
    }
```

# Intrinsic dimensionality

- Use PCA
- Fraction of variance explained for each PC
  - considere the ones >1%

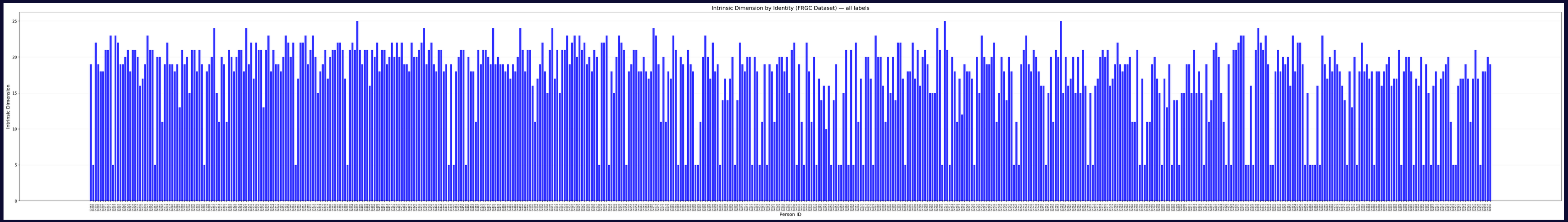
```python
intrinsic_dim = {}
for lbl, cluster in identity_clusters.items():
    if len(cluster) < 2: #do nothing
        continue
    pca = PCA(n_components=min(len(cluster), cluster.shape[1])) #min(len cluster and 512D)
    pca.fit(cluster)
    intrinsic_dim[label_names[lbl]] = np.sum(pca.explained_variance_ratio_ > 0.01)
```

# Intrinsic dimensionality

- Use PCA
- Fraction of variance explained for each PC
  - considere the ones >1%

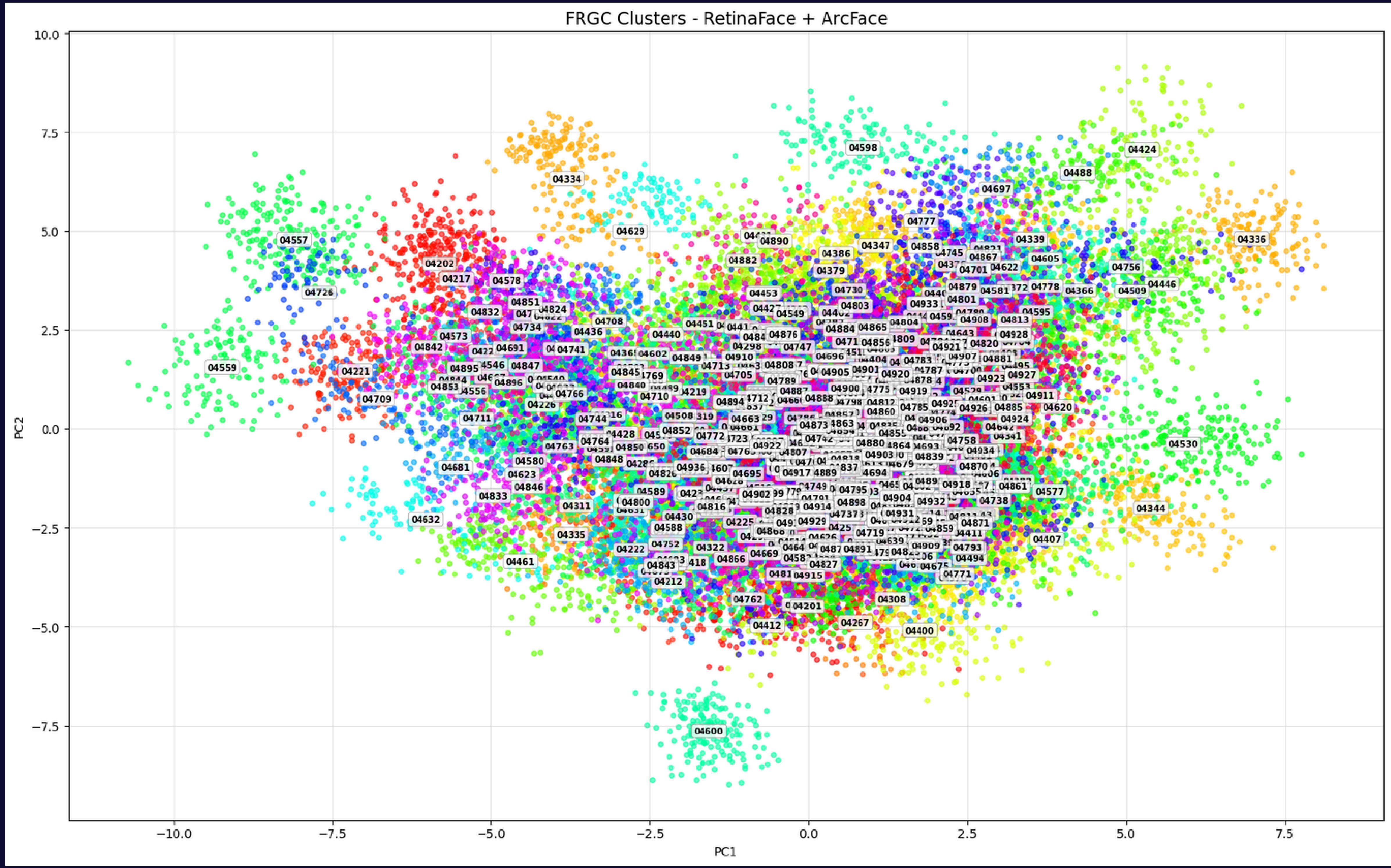
```python
intrinsic_dim = {}
for lbl, cluster in identity_clusters.items():
    if len(cluster) < 2: #do nothing
        continue
    pca = PCA(n_components=min(len(cluster), cluster.shape[1])) #min(len cluster and 512D)
    pca.fit(cluster)
    intrinsic_dim[label_names[lbl]] = np.sum(pca.explained_variance_ratio_ > 0.01)
```

```
Identity: 02463, Intrinsic Dimension: 19
Identity: 04200, Intrinsic Dimension: 5
Identity: 04201, Intrinsic Dimension: 22
Identity: 04202, Intrinsic Dimension: 19
Identity: 04203, Intrinsic Dimension: 18
Identity: 04207, Intrinsic Dimension: 18
Identity: 04211, Intrinsic Dimension: 21
Identity: 04212, Intrinsic Dimension: 21
Identity: 04213, Intrinsic Dimension: 23
Identity: 04214, Intrinsic Dimension: 5
Identity: 04217, Intrinsic Dimension: 23
Identity: 04219, Intrinsic Dimension: 22
Identity: 04221, Intrinsic Dimension: 19
Identity: 04222, Intrinsic Dimension: 19
Identity: 04225, Intrinsic Dimension: 20
Identity: 04226, Intrinsic Dimension: 21
Identity: 04227, Intrinsic Dimension: 18
Identity: 04228, Intrinsic Dimension: 21
Identity: 04229, Intrinsic Dimension: 21
Identity: 04233, Intrinsic Dimension: 20
Identity: 04236, Intrinsic Dimension: 16
Identity: 04237, Intrinsic Dimension: 17
Identity: 04239, Intrinsic Dimension: 19
Identity: 04243, Intrinsic Dimension: 23
Identity: 04252, Intrinsic Dimension: 21
...
```



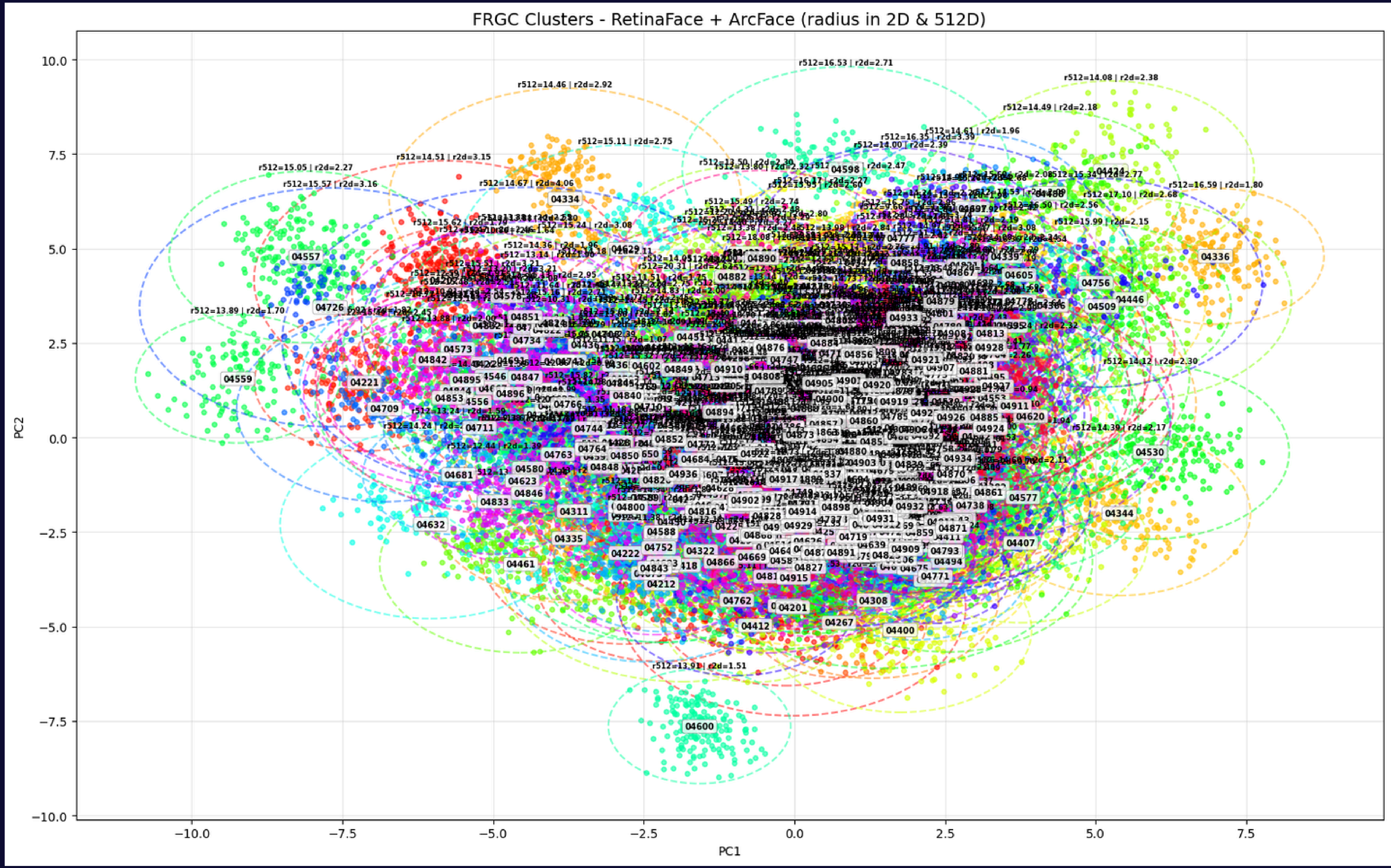
# Visualization Clusters

- Use PCA to pass the embeddings, centroids to 2D



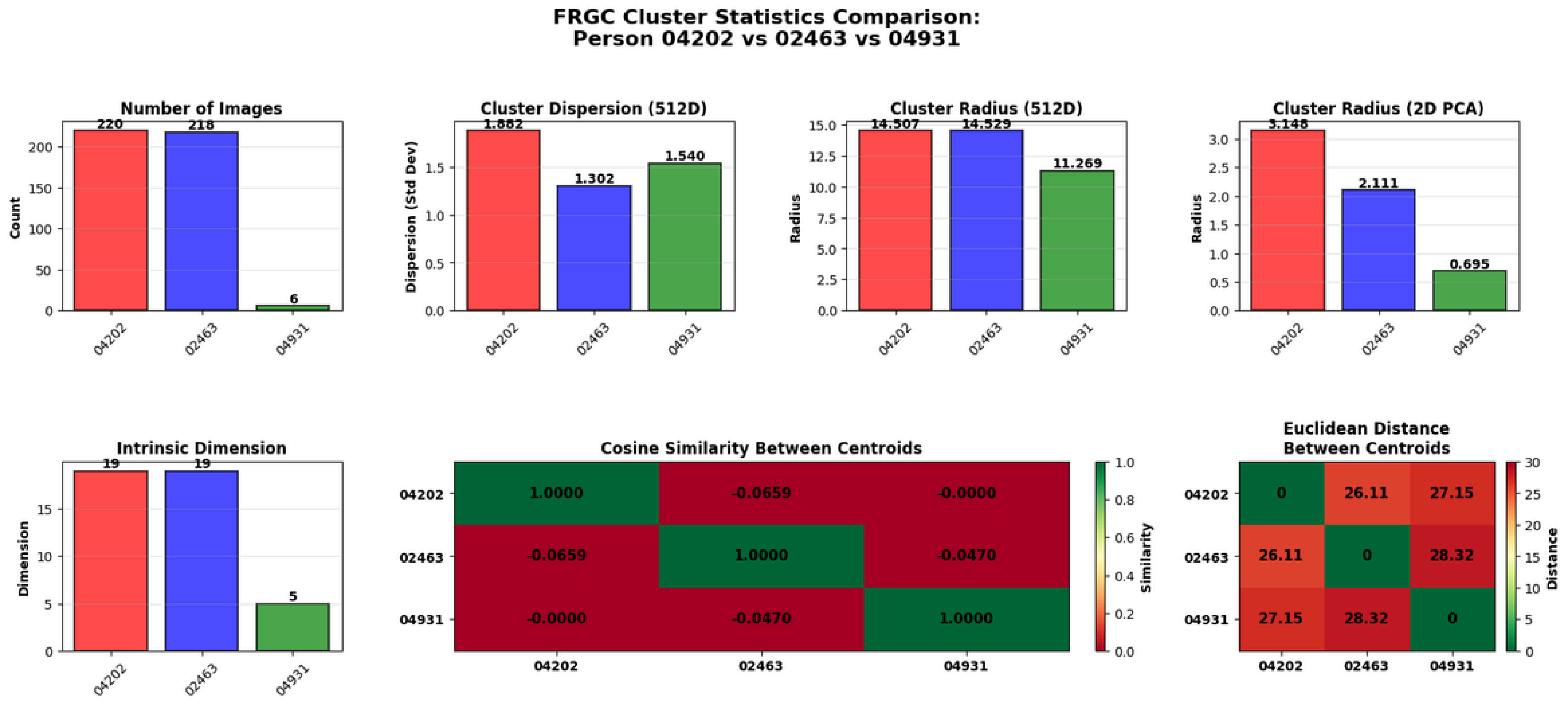
# Visualization Clusters

- Use PCA to pass the radius to 2D

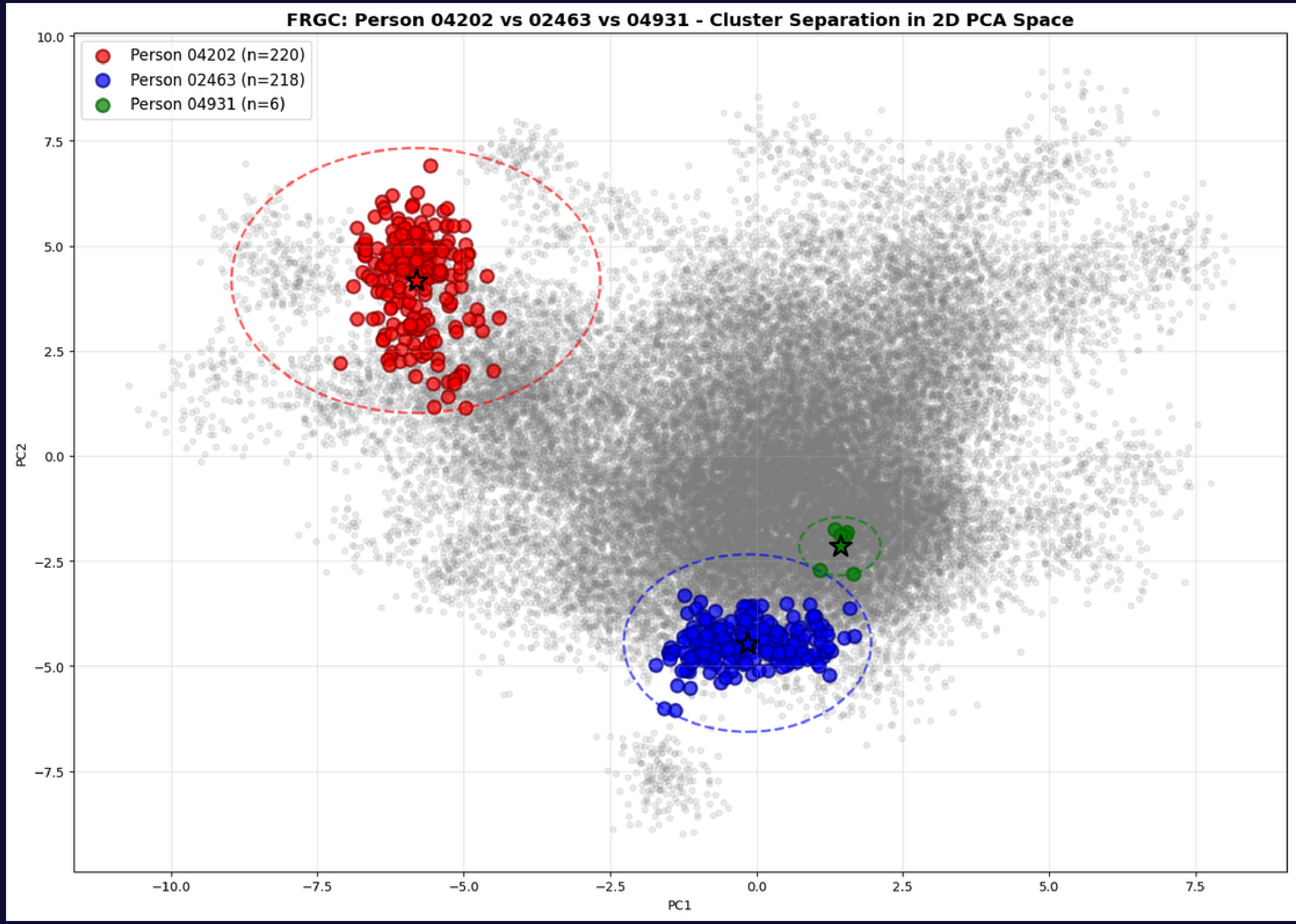


# Top 2 most imgs & least imgs

```
Person 04202 (Label 3): 220 images in dataset
Person 02463 (Label 0): 218 images in dataset
Person 04931 (Label 563): 6 images in dataset
```



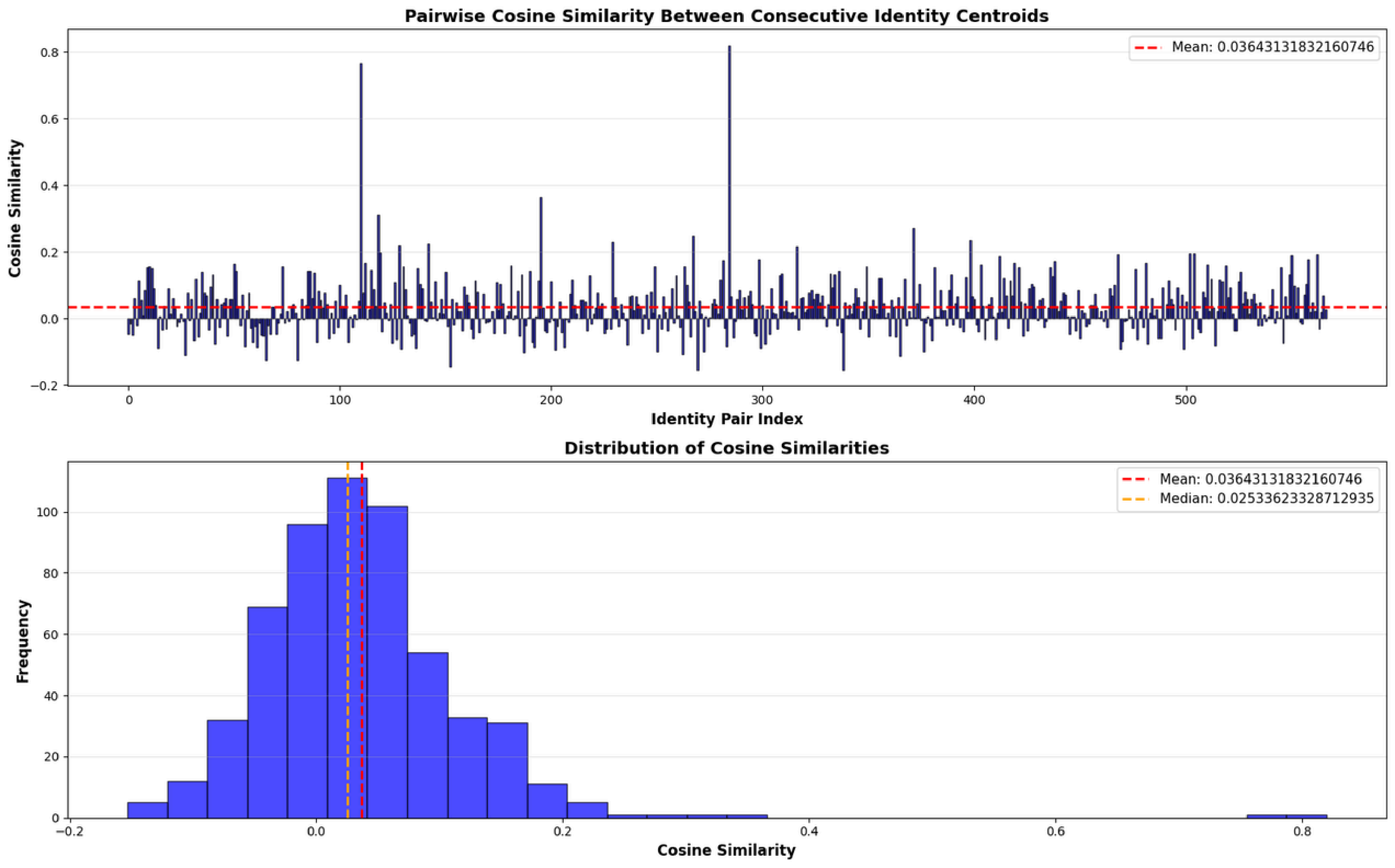

| Metric | Person 04202 | Person 02463 | Person 04931 |
|---|---|---|---|
| Number of Images | 220 | 218 | 6 |
| Radius (512D) | 14.506602631599486 | 14.529445198064755 | 11.269393211155041 |
| Dispersion (512D) | 1.8821422014891271 | 1.302409623588808 | 1.5401442839311412 |
| Intrinsic Dimension | 19 | 19 | 5 |
| Radius (2D PCA) | 3.148465410093664 | 2.111407381166888 | 0.6949382401039255 |



# Cosine similarity between clusters

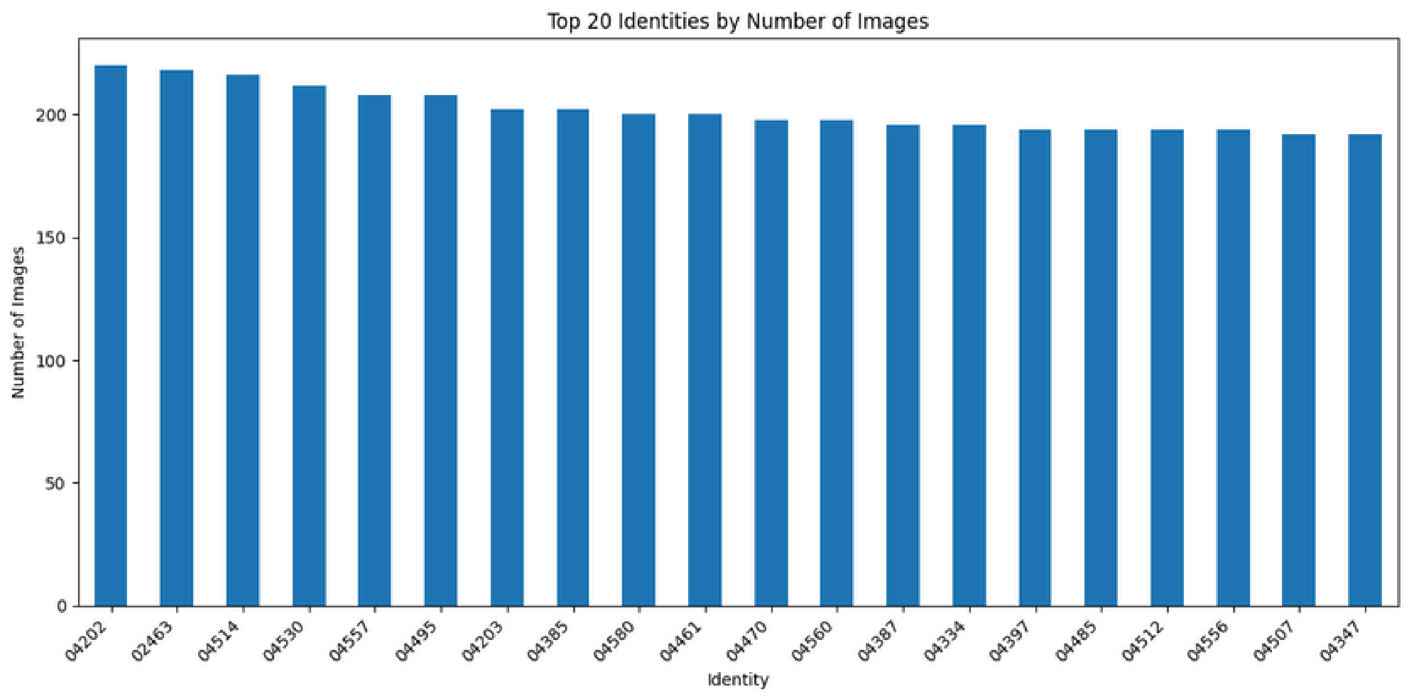
```
Cosine similarity 02463 vs 04200: -0.04679897054417177
Cosine similarity 04200 vs 04201: -0.013916435165089124
Cosine similarity 04201 vs 04202: -0.048344078385030353
Cosine similarity 04202 vs 04203: 0.06100253357088985
Cosine similarity 04203 vs 04207: -0.02003149352578509
Cosine similarity 04207 vs 04211: 0.11562369699844235
Cosine similarity 04211 vs 04212: 0.055733873253226325
Cosine similarity 04212 vs 04213: 0.00919782503036624
Cosine similarity 04213 vs 04214: 0.08525917496654231
Cosine similarity 04214 vs 04217: 0.153418398442527
Cosine similarity 04217 vs 04219: 0.1571779881157469
Cosine similarity 04219 vs 04221: 0.15038013495742253
Cosine similarity 04221 vs 04222: 0.09108343973416647
Cosine similarity 04222 vs 04225: 0.041311963652886835
Cosine similarity 04225 vs 04226: -0.08884062578377462
Cosine similarity 04226 vs 04227: 0.005188142806347919
Cosine similarity 04227 vs 04228: -0.03393942881313773
Cosine similarity 04228 vs 04229: 0.03830991167003205
Cosine similarity 04229 vs 04233: -0.030275379732603372
Cosine similarity 04233 vs 04236: 0.0918104127700984
Cosine similarity 04236 vs 04237: 0.014143682455215387
Cosine similarity 04237 vs 04239: 0.061534903623247005
Cosine similarity 04239 vs 04243: 0.029727282797203672
Cosine similarity 04243 vs 04252: -0.02315841111273054
Cosine similarity 04252 vs 04256: -0.008843094425232734
...
```

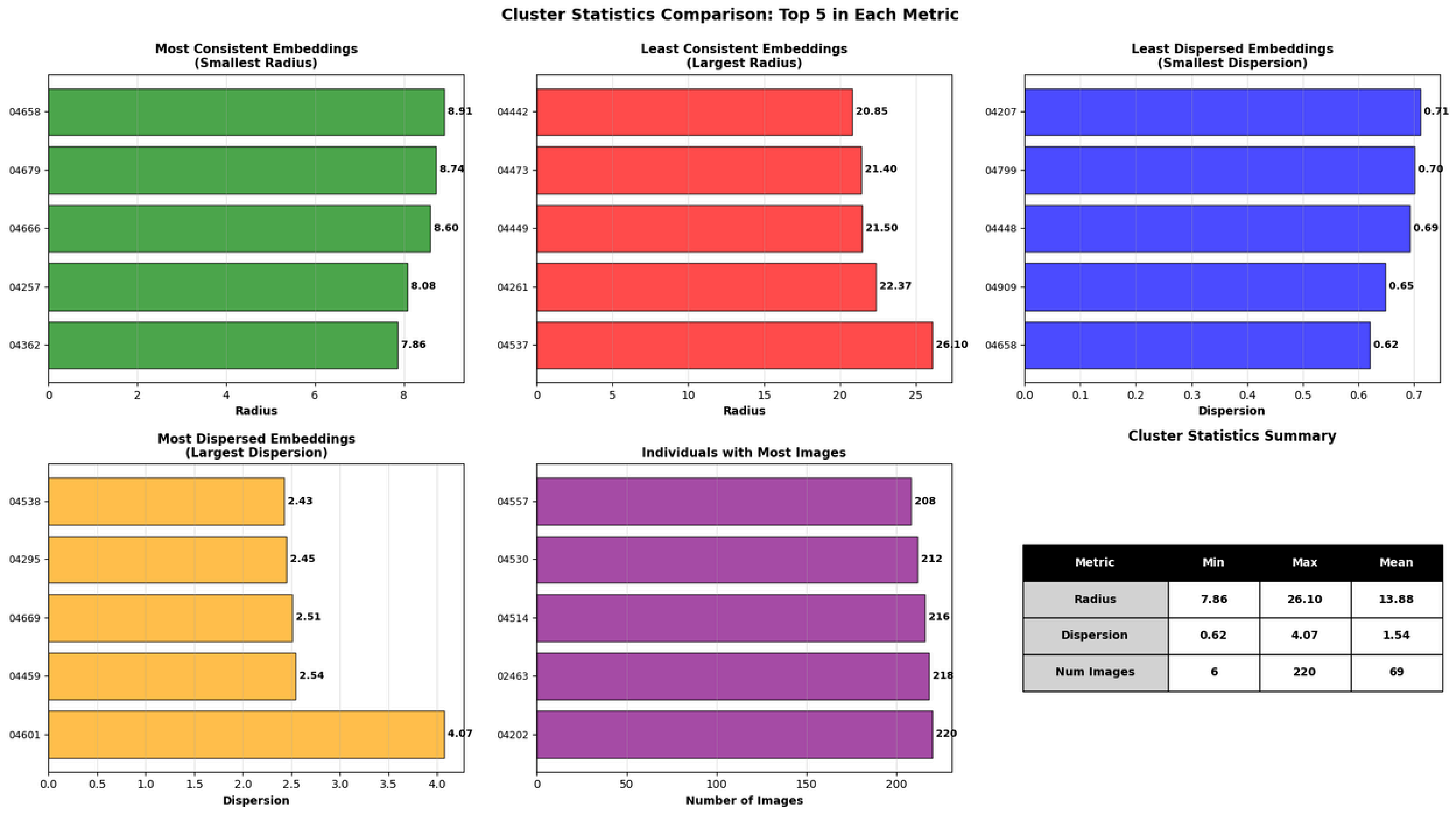
```
======================================================================
COSINE SIMILARITY STATISTICS (Consecutive Pairs):
======================================================================
Mean similarity: 0.03643131832160746
Median similarity: 0.02533623328712935
Std deviation: 0.08469321468319657
Min similarity: -0.15329670729608094
Max similarity: 0.8199336296871338
```



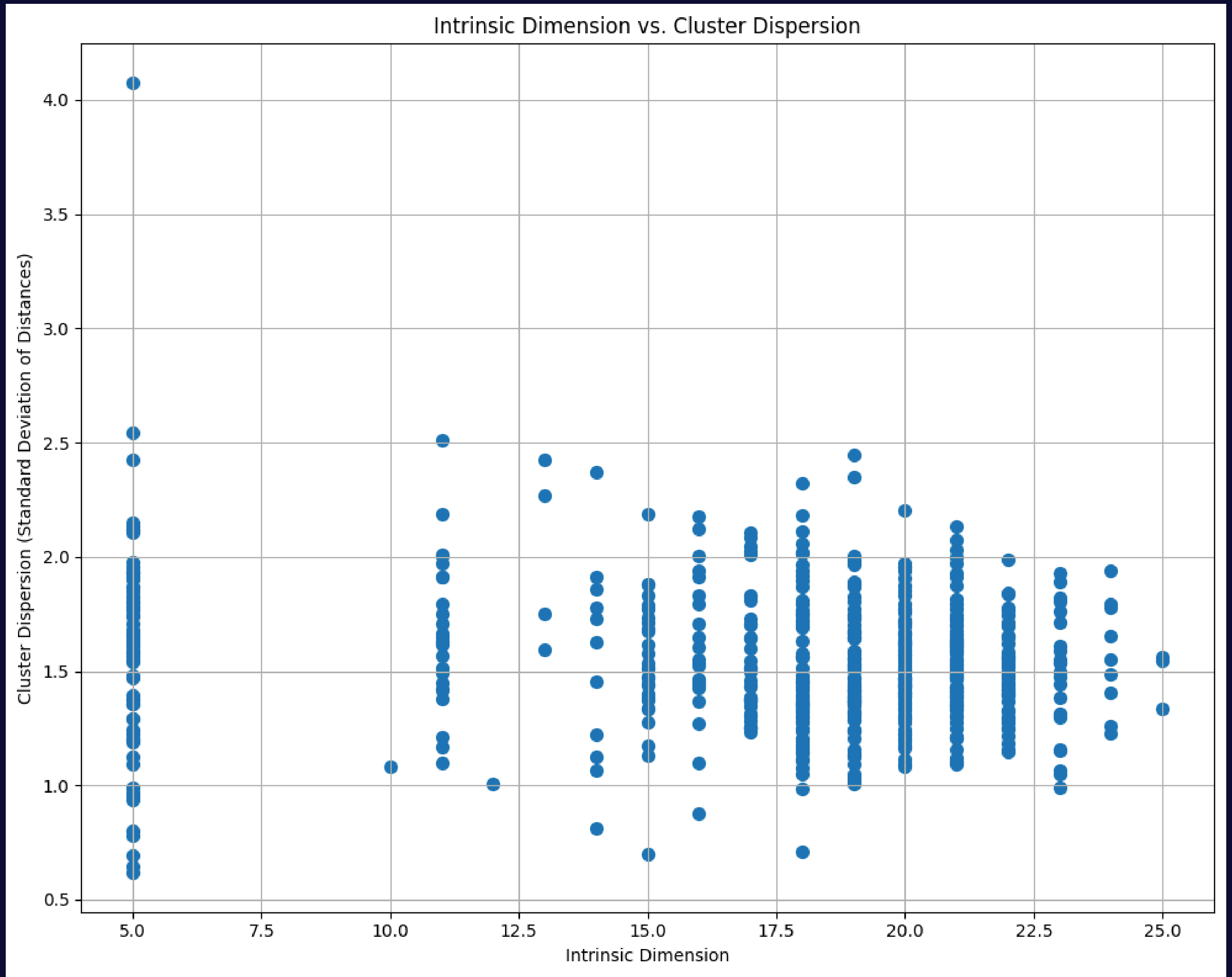
# Analyze cluster stats

```
Summary Statistics for Merged DataFrame:
       intrinsic_dimension      radius  dispersion  num_images
count           568.000000  568.000000  568.000000  568.000000
mean             17.102113   13.880613    1.539555   69.237676
std               5.313468    2.138281    0.317522   53.826341
min               5.000000    7.856437    0.620193    6.000000
25%              16.000000   12.748964    1.350966   24.000000
50%              19.000000   13.918478    1.514161   60.000000
75%              21.000000   15.013691    1.723253   97.000000
max              25.000000   26.103618    4.073384  220.000000
```

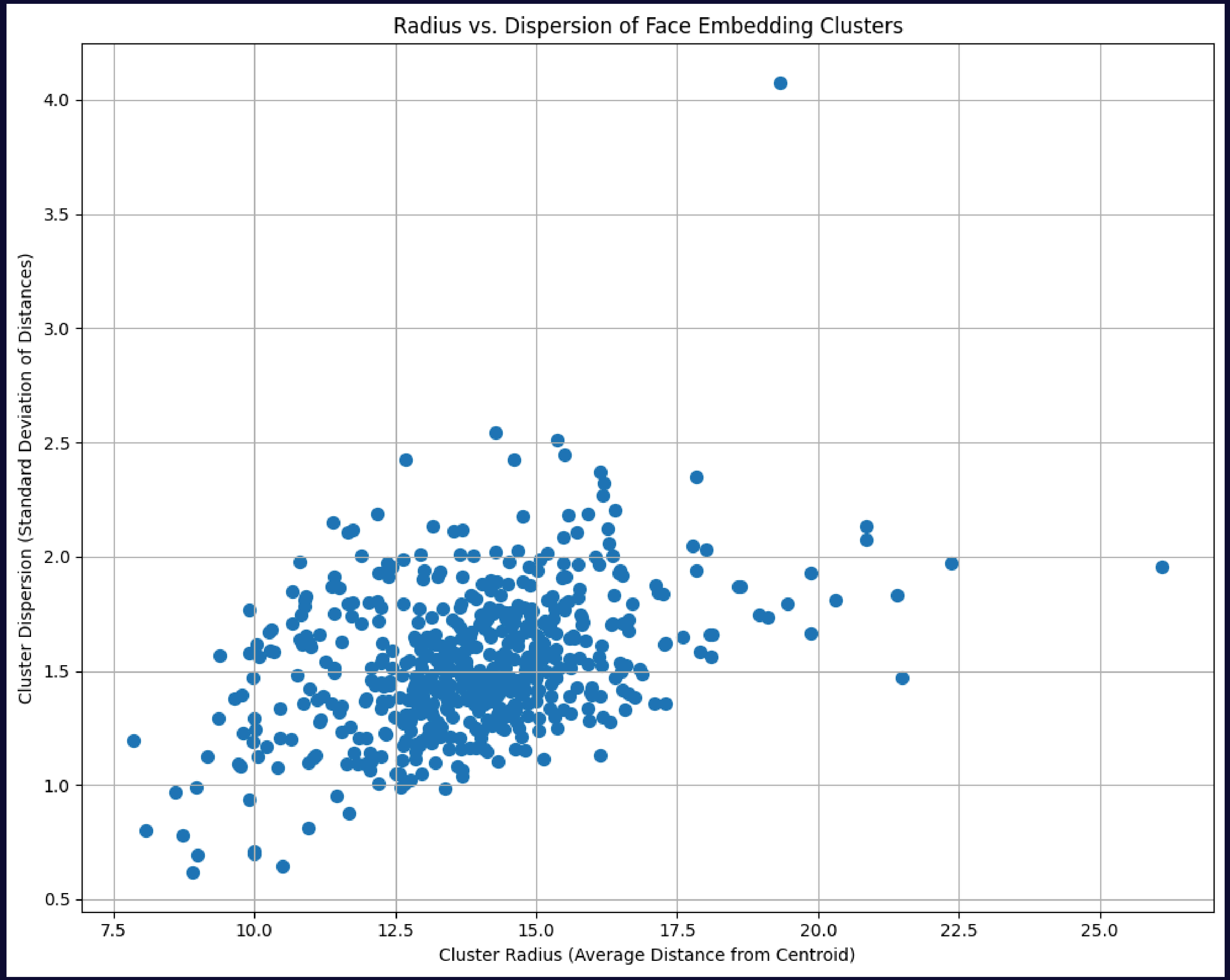


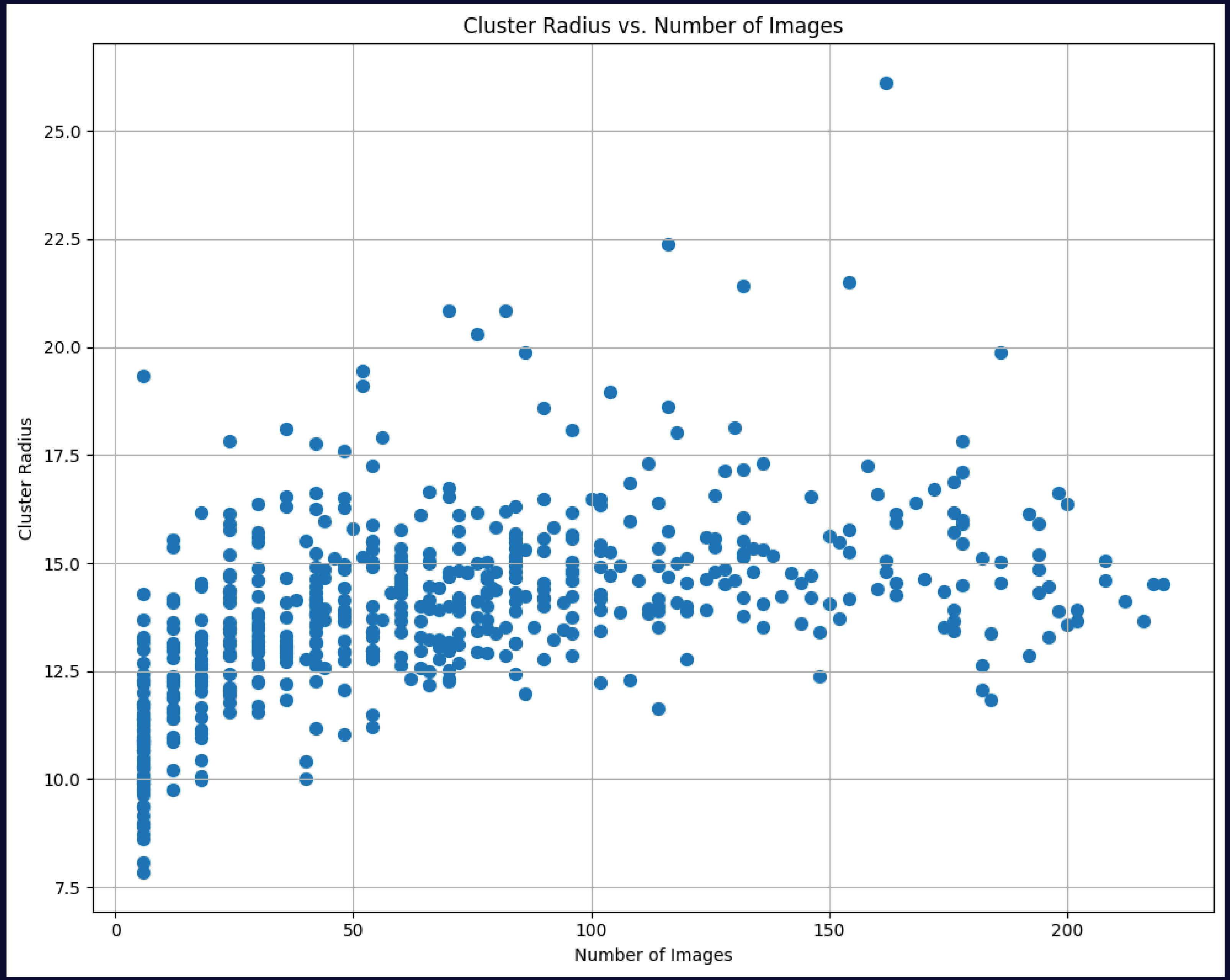
# Scatter Plot: Intrinsic Dimension vs Cluster Dispersion



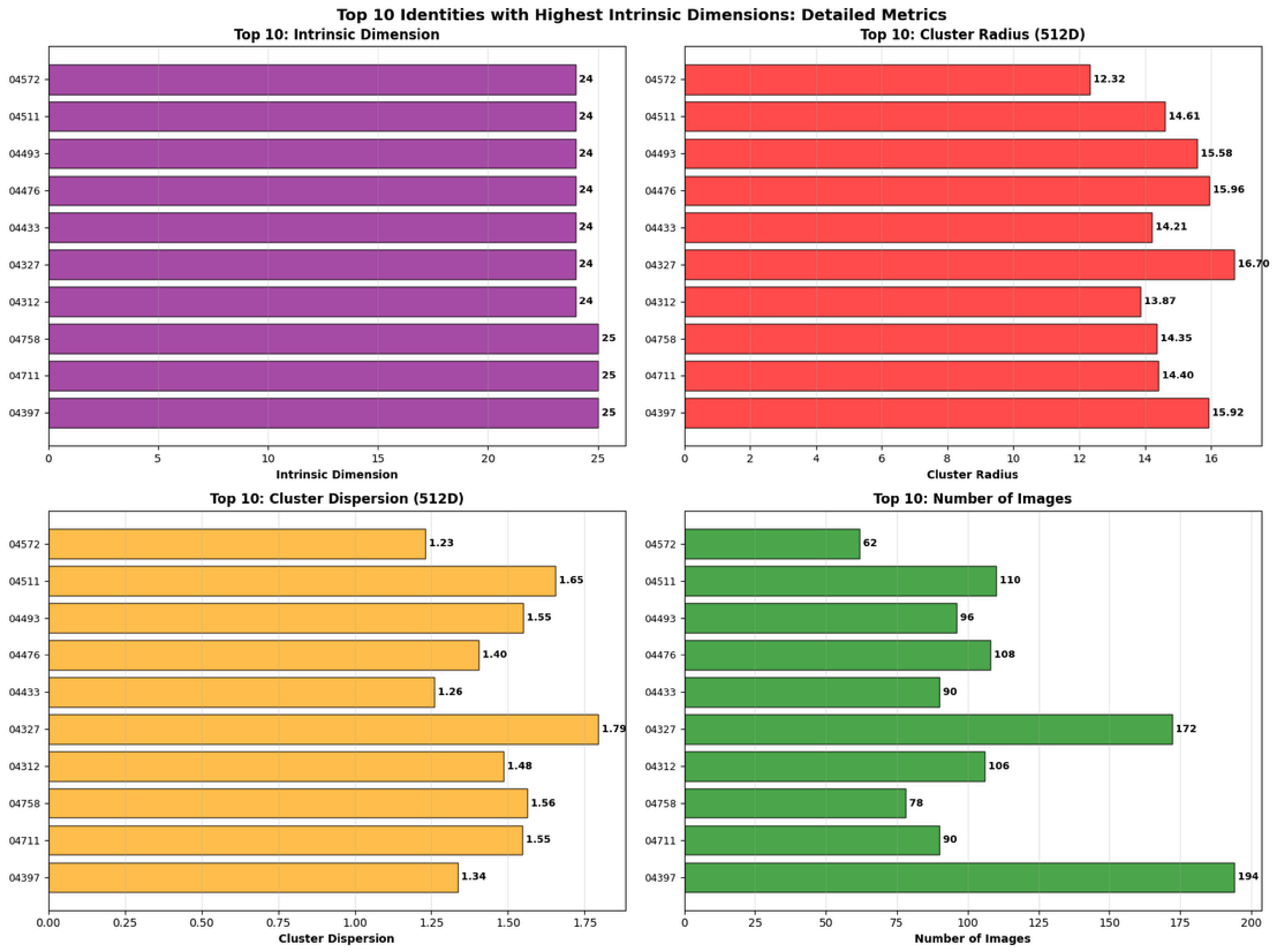
# Scatter Plot: Radius vs Dispersion



# Scatter Plot: Intrinsic Radius vs Number of Imgs



# Intrinsic Dimension of Clusters




```
Identities with the 10 highest intrinsic dimensions:
       intrinsic_dimension
04397                   25
04758                   25
04711                   25
04433                   24
04511                   24
04327                   24
04312                   24
04708                   24
04839                   24
04493                   24
...
04586                    5
04391                    5
04835                    5
04306                    5
```

### Top 10 Identities with Highest Intrinsic Dimensions

| Identity | Intrinsic Dim | Radius | Dispersion | Num Images |
|---|---|---|---|---|
| 04397 | 25 | 15.92 | 1.34 | 194 |
| 04711 | 25 | 14.40 | 1.55 | 90 |
| 04758 | 25 | 14.35 | 1.56 | 78 |
| 04312 | 24 | 13.87 | 1.48 | 106 |
| 04327 | 24 | 16.70 | 1.79 | 172 |
| 04433 | 24 | 14.21 | 1.26 | 90 |
| 04476 | 24 | 15.96 | 1.40 | 108 |
| 04493 | 24 | 15.58 | 1.55 | 96 |
| 04511 | 24 | 14.61 | 1.65 | 110 |
| 04572 | 24 | 12.32 | 1.23 | 62 |

### Cluster Statistics Summary

| Metric | Max | Min | Mean |
|---|---|---|---|
| Radius (512D) | 26.10 | 7.86 | 13.88 |
| Dispersion | 4.07 | 0.62 | 1.54 |
| Num Images | 220 | 6 | 69 |

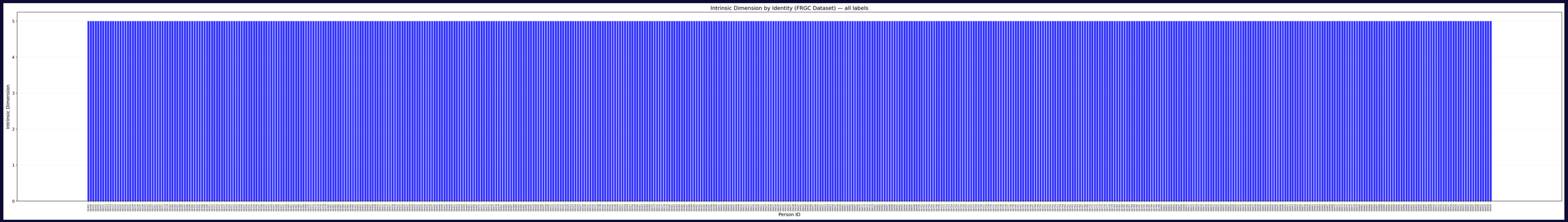
# Friday

23th January

Filter by the same number of imgs each one

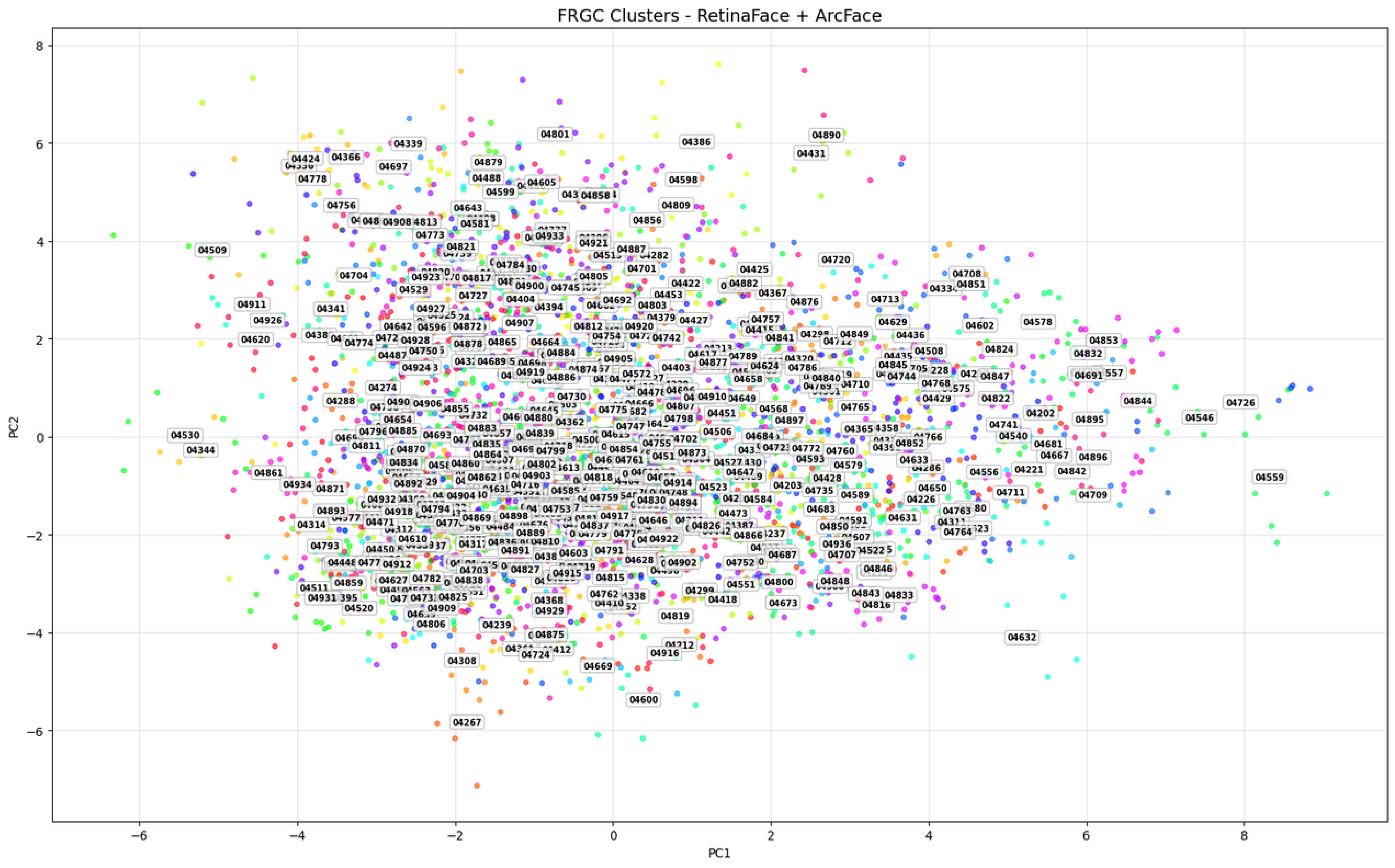
# Intrinsic dimensionality

```
Identity: 02463, Intrinsic Dimension: 5
Identity: 04200, Intrinsic Dimension: 5
Identity: 04201, Intrinsic Dimension: 5
Identity: 04202, Intrinsic Dimension: 5
Identity: 04203, Intrinsic Dimension: 5
Identity: 04207, Intrinsic Dimension: 5
Identity: 04211, Intrinsic Dimension: 5
Identity: 04212, Intrinsic Dimension: 5
Identity: 04213, Intrinsic Dimension: 5
Identity: 04214, Intrinsic Dimension: 5
Identity: 04217, Intrinsic Dimension: 5
Identity: 04219, Intrinsic Dimension: 5
Identity: 04221, Intrinsic Dimension: 5
Identity: 04222, Intrinsic Dimension: 5
Identity: 04225, Intrinsic Dimension: 5
Identity: 04226, Intrinsic Dimension: 5
Identity: 04227, Intrinsic Dimension: 5
Identity: 04228, Intrinsic Dimension: 5
Identity: 04229, Intrinsic Dimension: 5
Identity: 04233, Intrinsic Dimension: 5
Identity: 04236, Intrinsic Dimension: 5
Identity: 04237, Intrinsic Dimension: 5
Identity: 04239, Intrinsic Dimension: 5
Identity: 04243, Intrinsic Dimension: 5
Identity: 04252, Intrinsic Dimension: 5
...
```



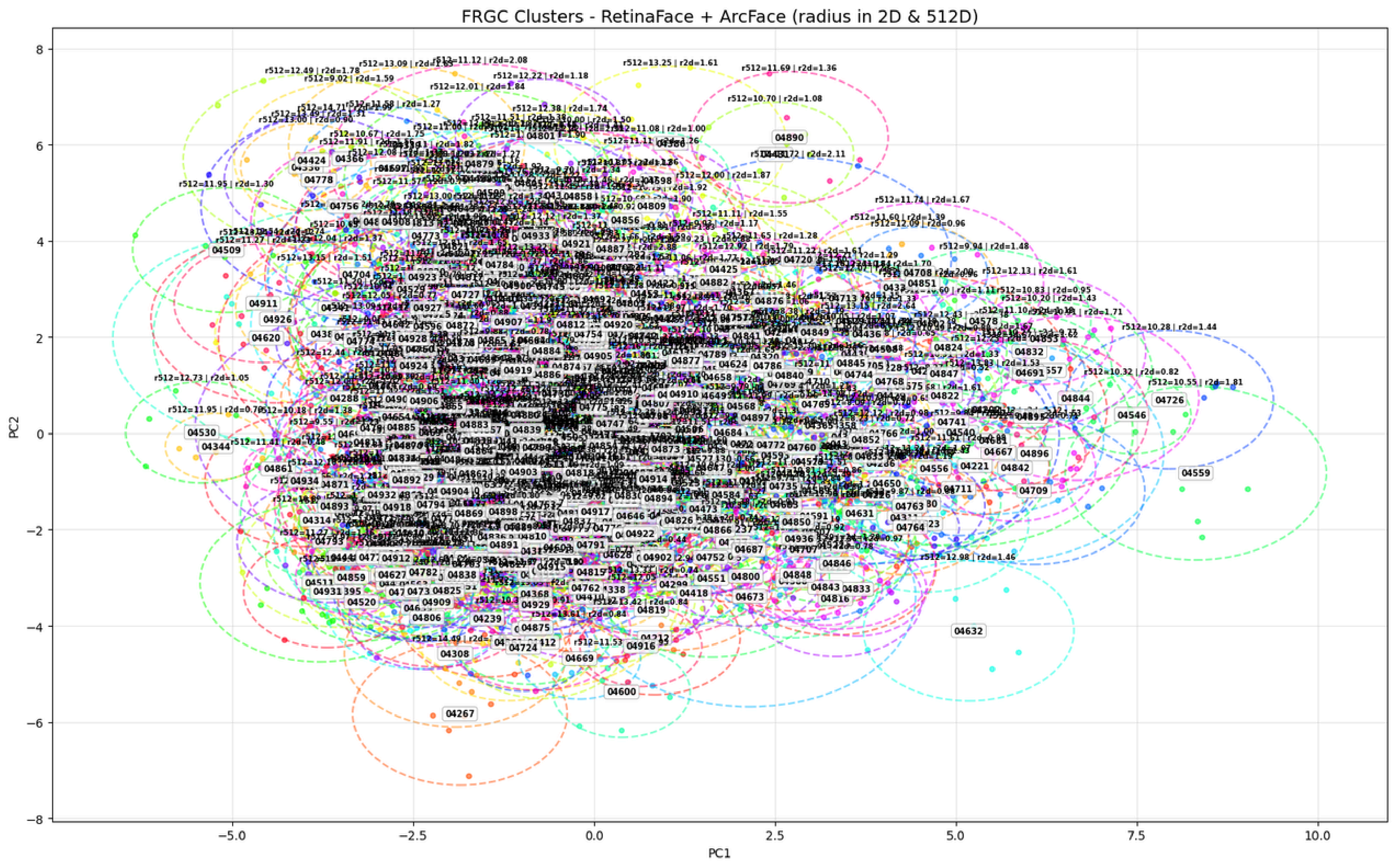
# Visualization Clusters

- Use PCA to pass the embeddings, centroids to 2D



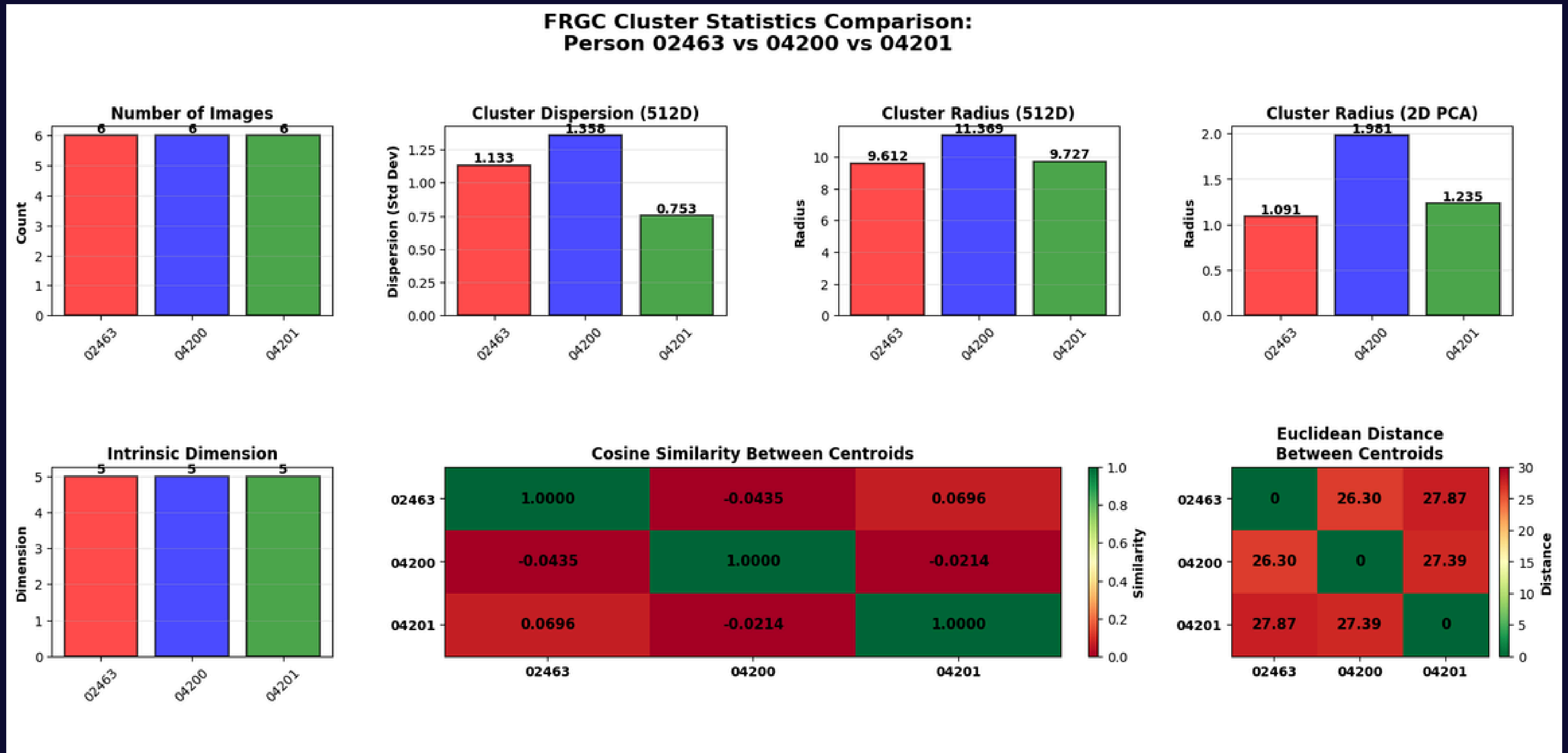
# Visualization Clusters

- Use PCA to pass the radius to 2D

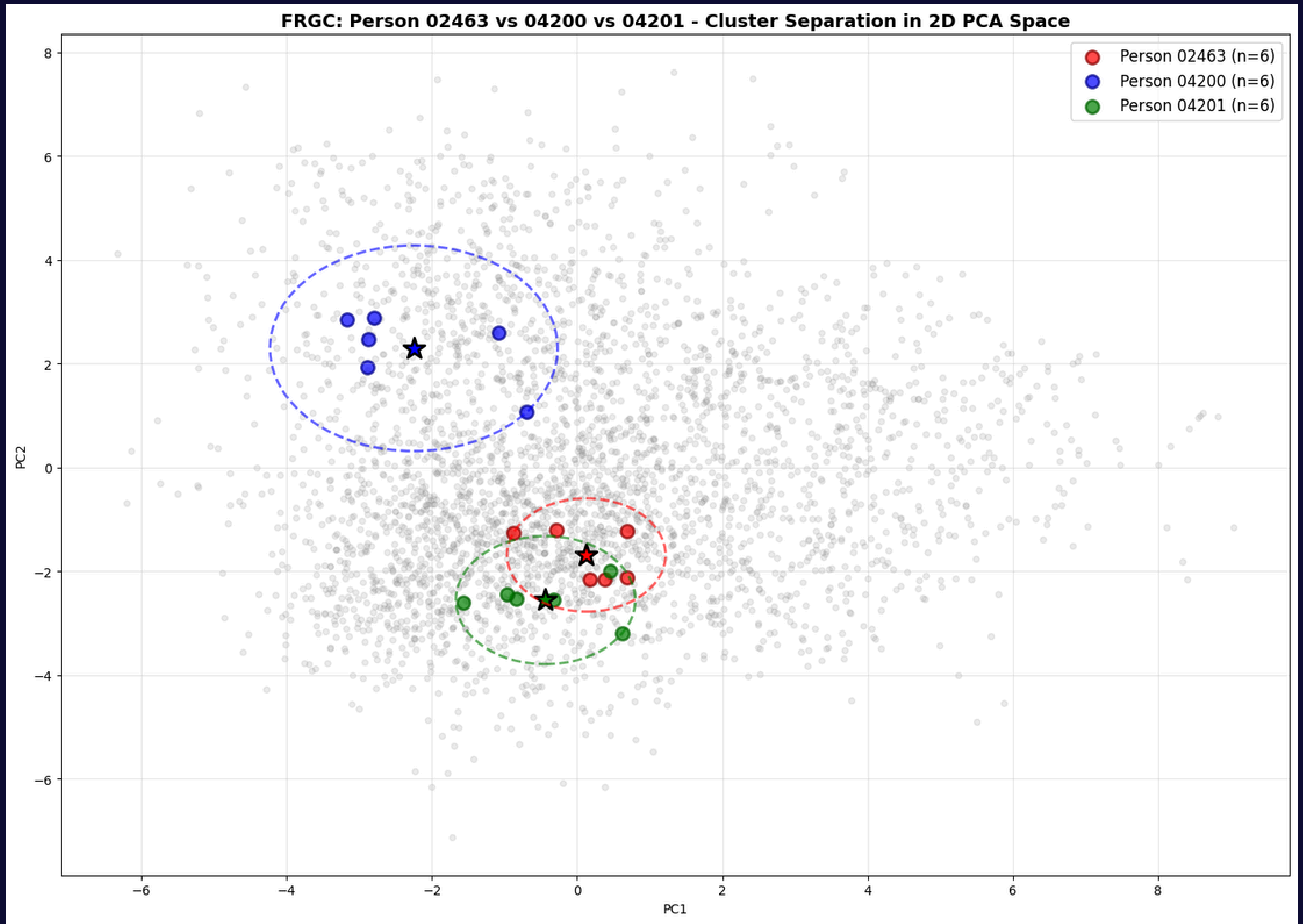


# Top 2 most imgs & least imgs

```
Person 02463 (Label 0): 6 images in dataset
Person 04200 (Label 1): 6 images in dataset
Person 04201 (Label 2): 6 images in dataset
```



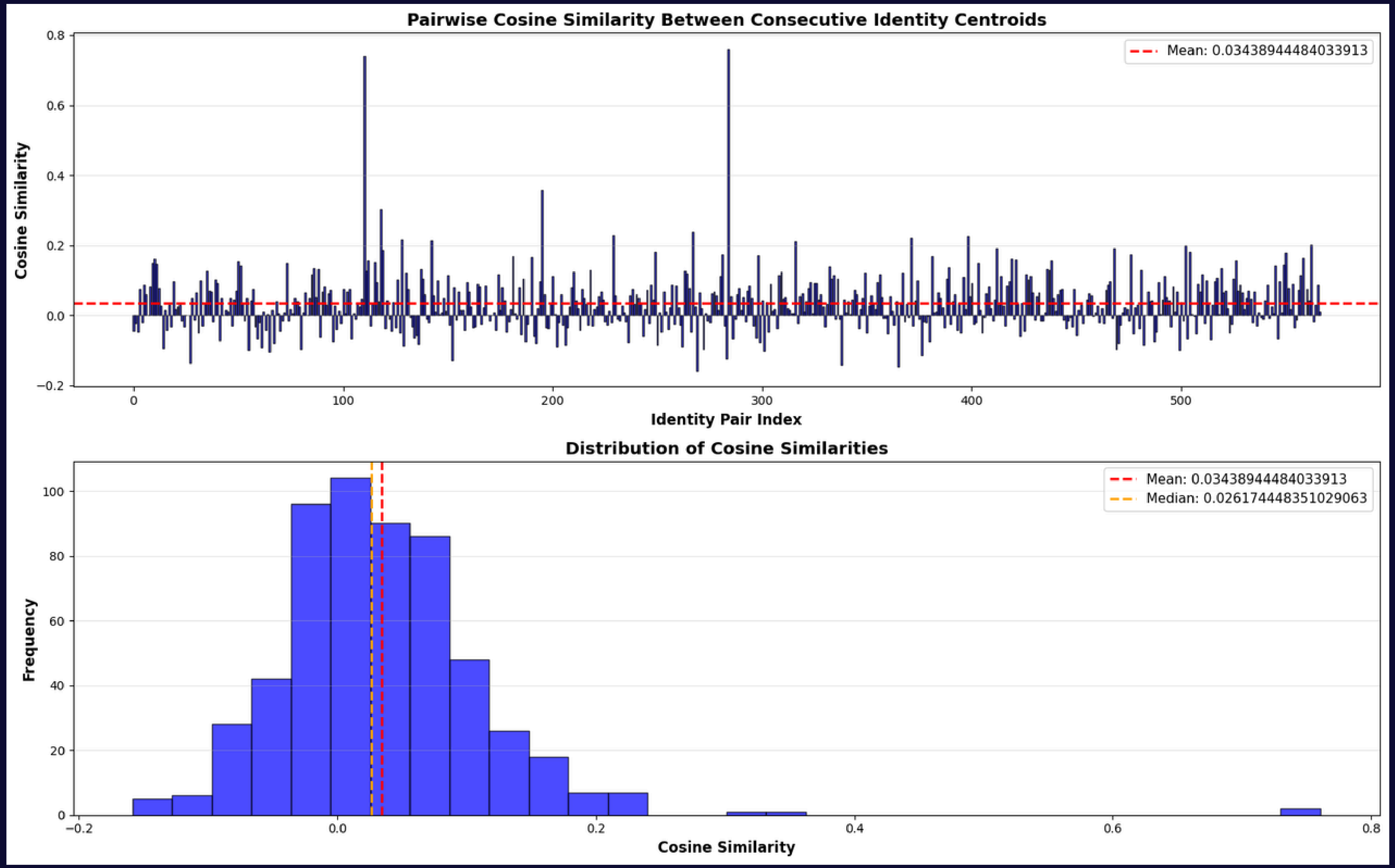

| Metric | Person 02463 | Person 04200 | Person 04201 |
|---|---|---|---|
| Number of Images | 6 | 6 | 6 |
| Radius (512D) | 9.611727488601367 | 11.369415615549324 | 9.727313695698973 |
| Dispersion (512D) | 1.1326423756206148 | 1.3577672665193006 | 0.7527016812639518 |
| Intrinsic Dimension | 5 | 5 | 5 |
| Radius (2D PCA) | 1.0909030870113223 | 1.9812208898109942 | 1.2349468004671176 |



# Cosine similarity between clusters

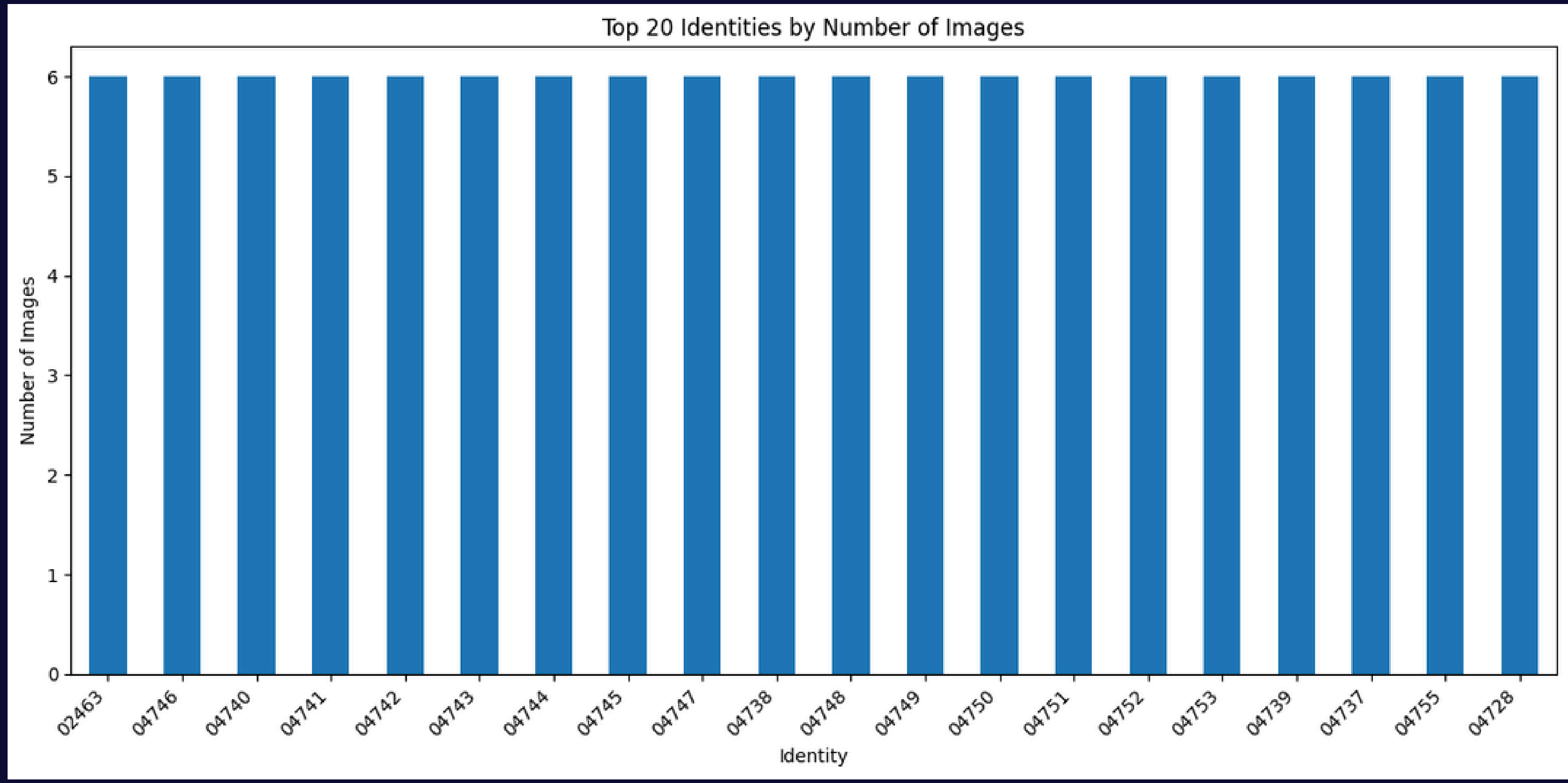
```
Cosine similarity 02463 vs 04200: -0.04352367760149198
Cosine similarity 04200 vs 04201: -0.021376891904623888
Cosine similarity 04201 vs 04202: -0.0465113332034324
Cosine similarity 04202 vs 04203: 0.07574114936923862
Cosine similarity 04203 vs 04207: -0.018798449078232637
Cosine similarity 04207 vs 04211: 0.08662288905644512
Cosine similarity 04211 vs 04212: 0.05876698446062904
Cosine similarity 04212 vs 04213: -0.0011515324835901092
Cosine similarity 04213 vs 04214: 0.08256253349280435
Cosine similarity 04214 vs 04217: 0.14795170457168993
Cosine similarity 04217 vs 04219: 0.16166038822960804
Cosine similarity 04219 vs 04221: 0.1474325384286807
Cosine similarity 04221 vs 04222: 0.07616846451022971
Cosine similarity 04222 vs 04225: 0.02657734309633825
Cosine similarity 04225 vs 04226: -0.09479351369269487
Cosine similarity 04226 vs 04227: 0.014401594978572463
Cosine similarity 04227 vs 04228: -0.0418653856818063
Cosine similarity 04228 vs 04229: 0.03093397017780001
Cosine similarity 04229 vs 04233: -0.03287943009342779
Cosine similarity 04233 vs 04236: 0.09693455921728633
Cosine similarity 04236 vs 04237: 0.018564433125425554
Cosine similarity 04237 vs 04239: 0.023943285180517124
Cosine similarity 04239 vs 04243: 0.031002959207787117
Cosine similarity 04243 vs 04252: -0.013732566019469615
Cosine similarity 04252 vs 04256: -0.03340927723057948
...
```

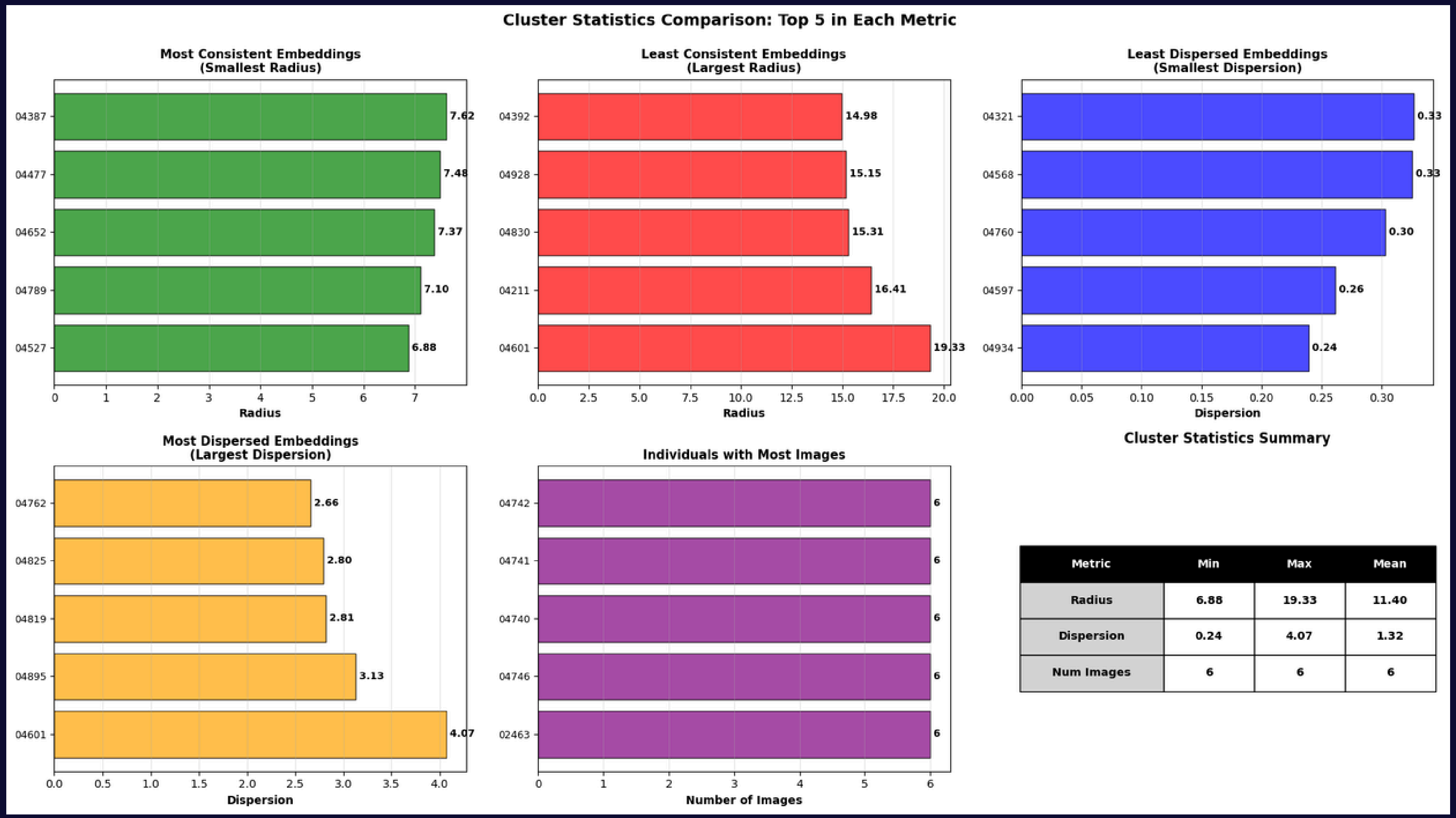
```
====================================================
COSINE SIMILARITY STATISTICS (Consecutive Pairs):
====================================================
Mean similarity: 0.03438944484033913
Median similarity: 0.026174448351029063
Std deviation: 0.0819512379294327
Min similarity: -0.1582380813054246
Max similarity: 0.7606668758685282
```



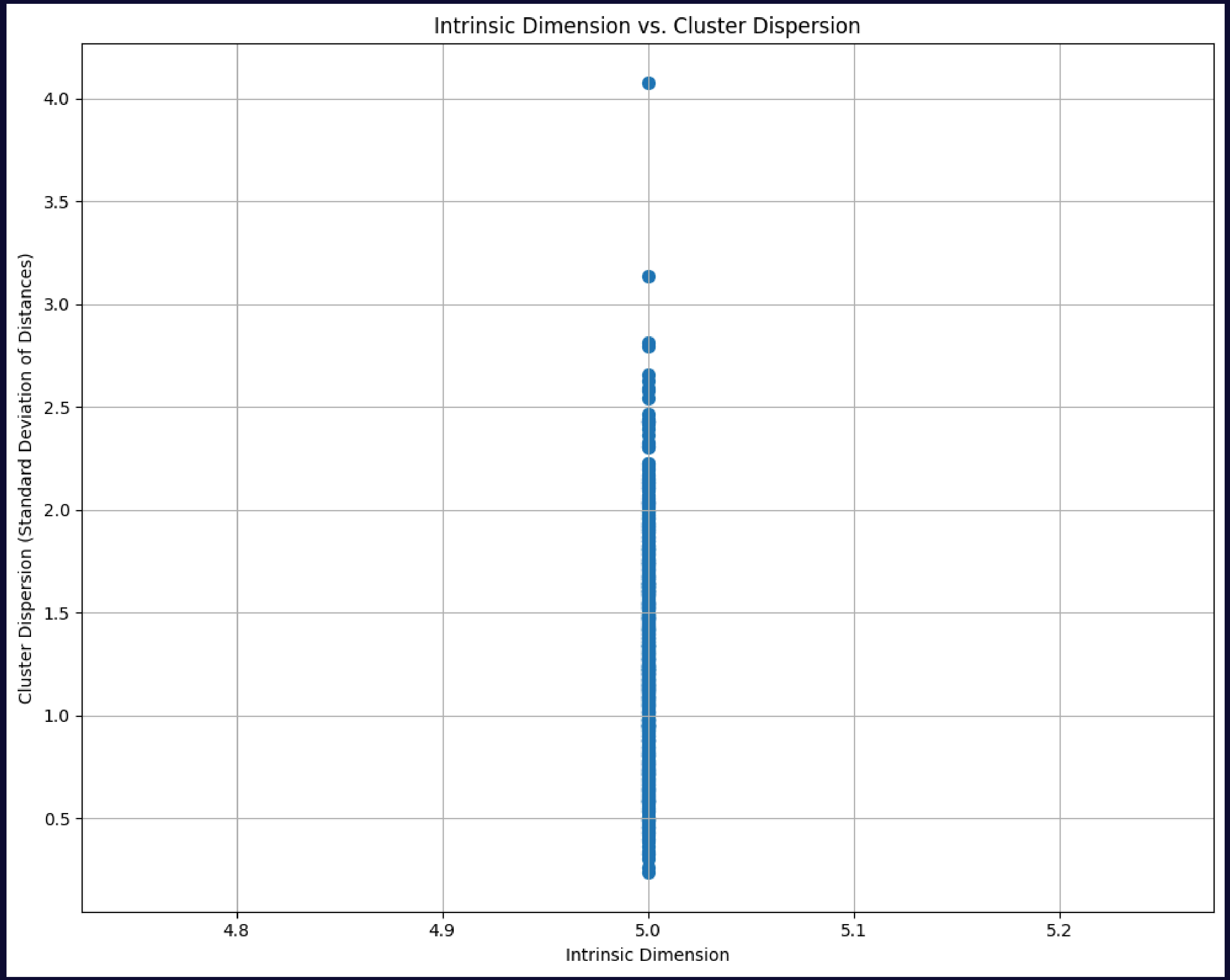
# Analyze cluster stats

```
Summary Statistics for Merged DataFrame:
       intrinsic_dimension      radius  dispersion  num_images
count                568.0  568.000000  568.000000       568.0
mean                   5.0   11.401431    1.321635         6.0
std                    0.0    1.424805    0.526045         0.0
min                    5.0    6.878414    0.239524         6.0
25%                    5.0   10.548006    0.949277         6.0
50%                    5.0   11.430022    1.289530         6.0
75%                    5.0   12.279211    1.660390         6.0
max                    5.0   19.326397    4.073384         6.0
```

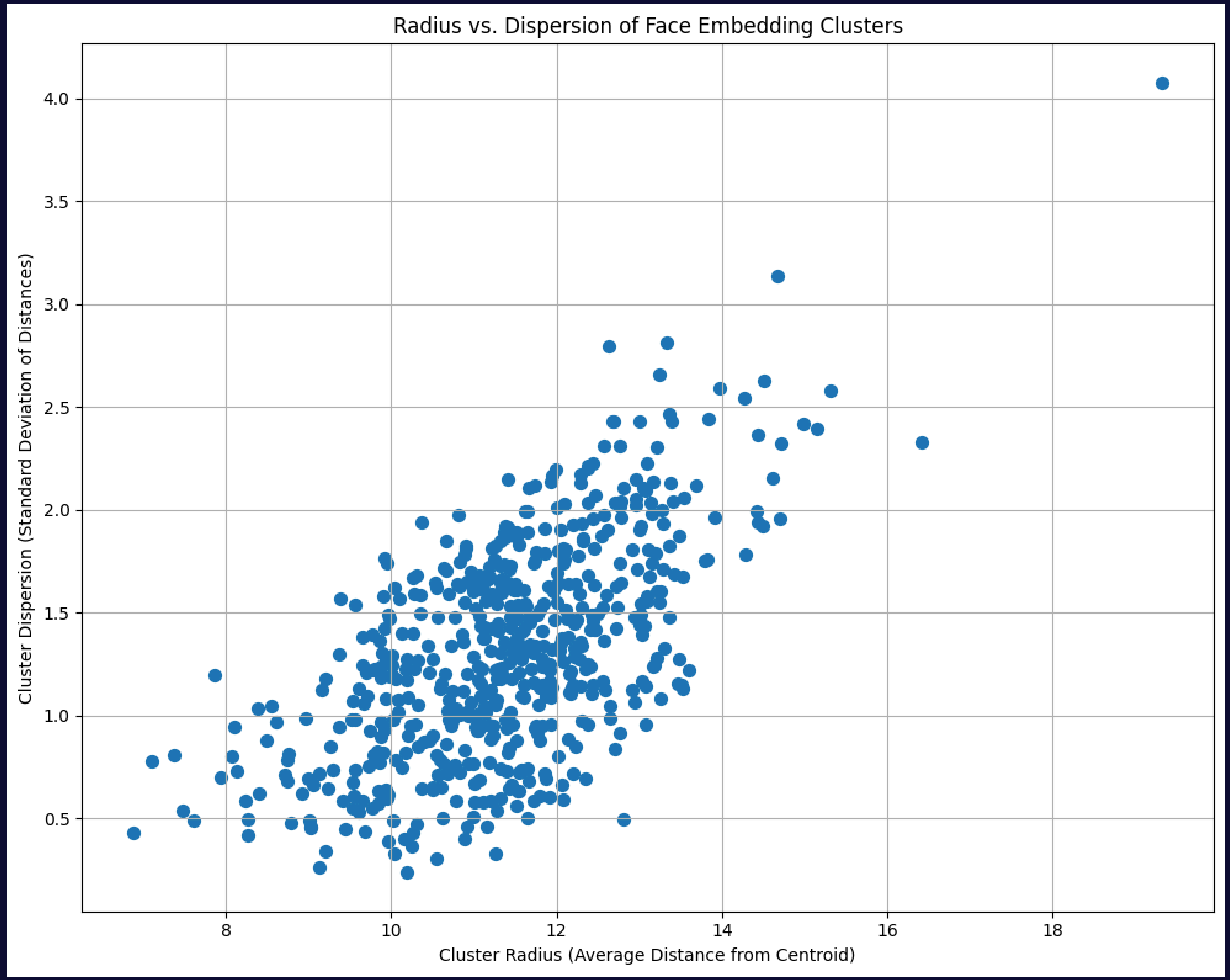


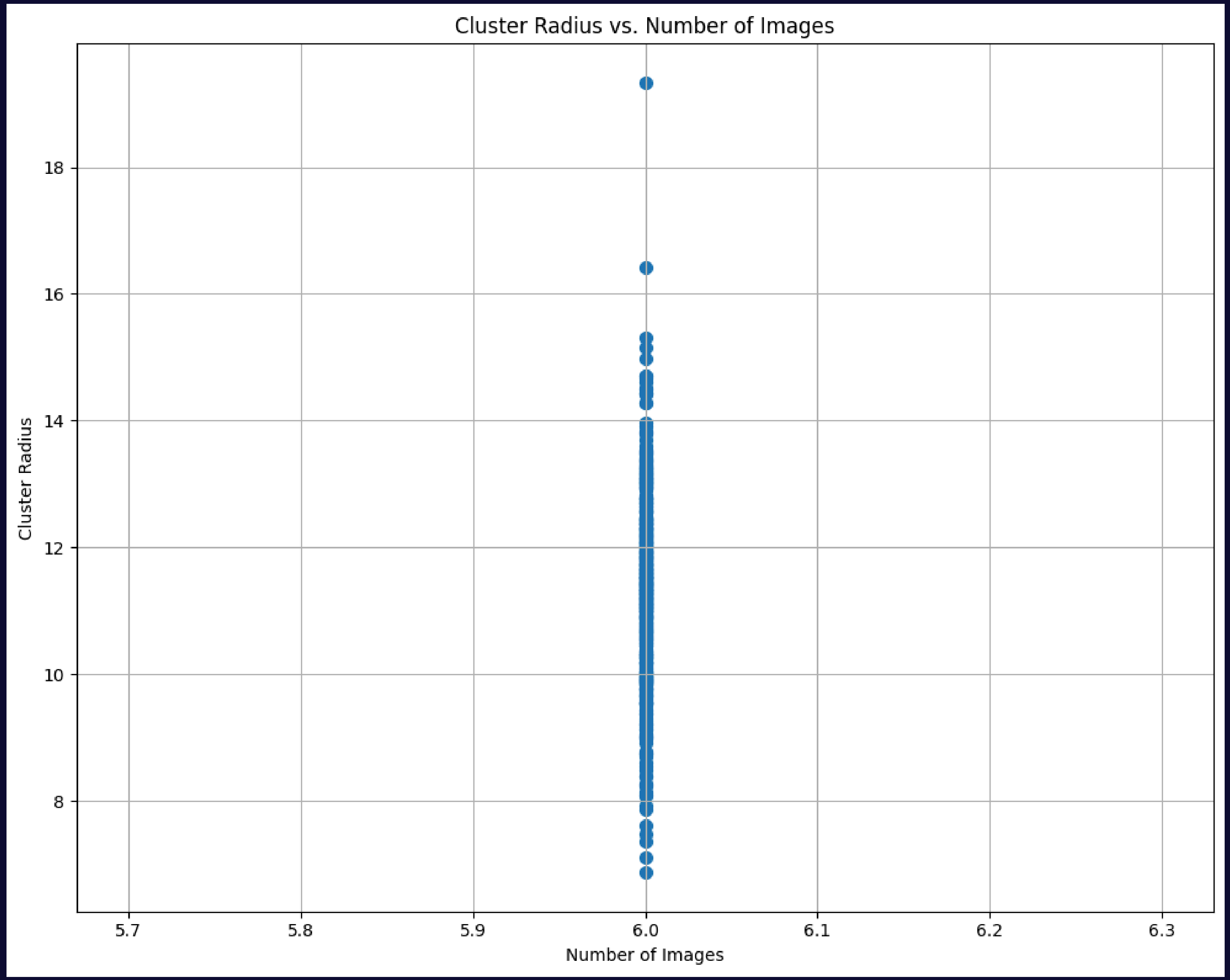
# Scatter Plot: Intrinsic Dimension vs Cluster Dispersion



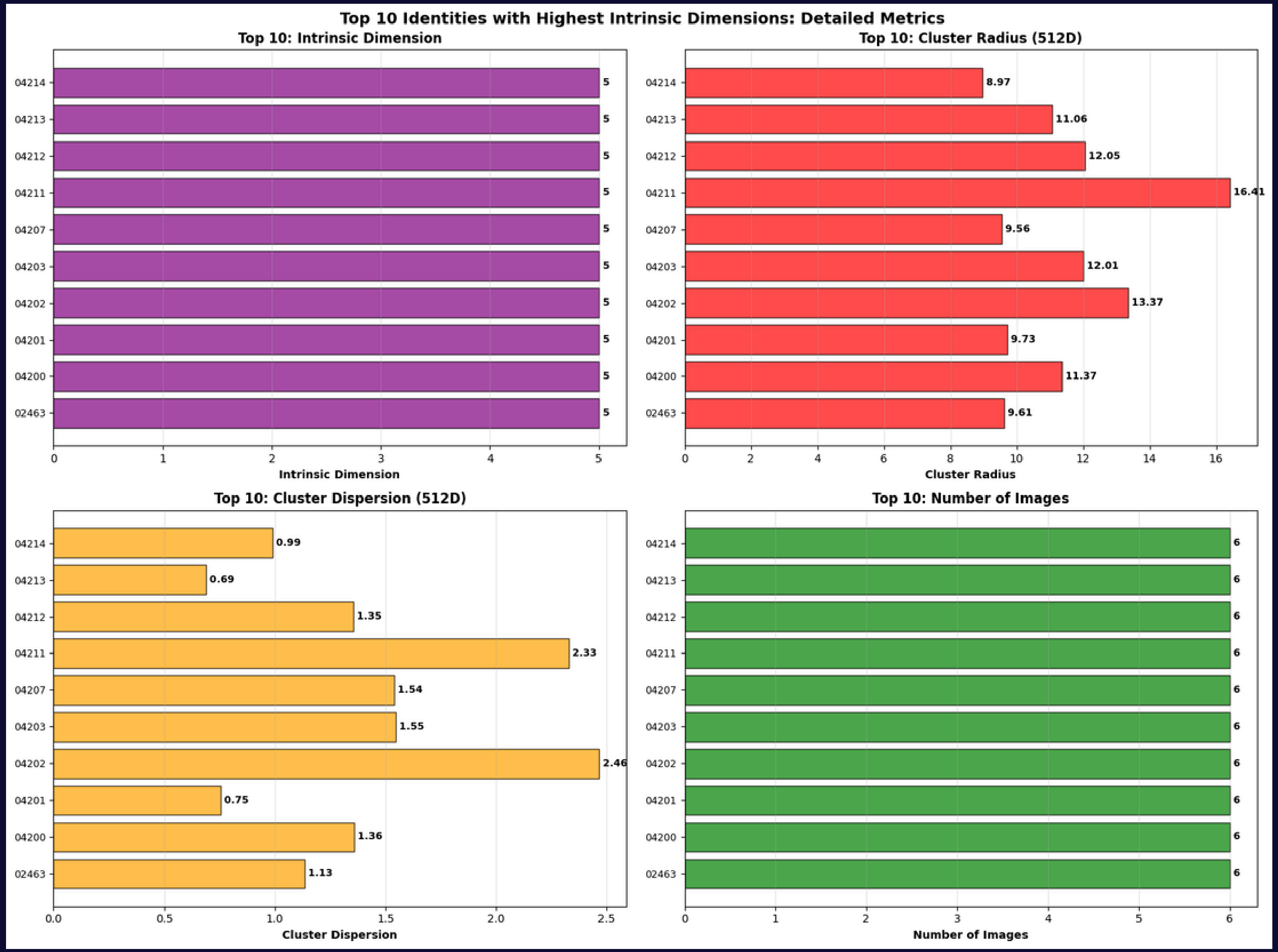
# Scatter Plot: Radius vs Dispersion



# Scatter Plot: Intrinsic Radius vs Number of Imgs



# Intrinsic Dimension of Clusters




```
Identities with the 10 highest intrinsic dimensions:
       intrinsic_dimension
02463                    5
04746                    5
04740                    5
04741                    5
04742                    5
04743                    5
04744                    5
04745                    5
04747                    5
04738                    5
...
04747                    5
04746                    5
04745                    5
04744                    5
```

**Top 10 Identities with Highest Intrinsic Dimensions**

| Identity | Intrinsic Dim | Radius | Dispersion | Num Images |
|---|---|---|---|---|
| 02463 | 5 | 9.61 | 1.13 | 6 |
| 04200 | 5 | 11.37 | 1.36 | 6 |
| 04201 | 5 | 9.73 | 0.75 | 6 |
| 04202 | 5 | 13.37 | 2.46 | 6 |
| 04203 | 5 | 12.01 | 1.55 | 6 |
| 04207 | 5 | 9.56 | 1.54 | 6 |
| 04211 | 5 | 16.41 | 2.33 | 6 |
| 04212 | 5 | 12.05 | 1.35 | 6 |
| 04213 | 5 | 11.06 | 0.69 | 6 |
| 04214 | 5 | 8.97 | 0.99 | 6 |

**Cluster Statistics Summary**

| Metric | Max | Min | Mean |
|---|---|---|---|
| Radius (512D) | 19.33 | 6.88 | 11.40 |
| Dispersion | 4.07 | 0.24 | 1.32 |
| Num Images | 6 | 6 | 6 |

# Saturday

24th January

# ToDo

- If you used a subset of frgc for those experiments, upgrade to all images, all subjects.
  - **I use all the images.**
- If you already did all, then please use the weekend to document everything well.
  - **Document in this PPT.**
- Package your code for a github repository.
  - **Done https://github.com/J0SEF4/The-Bridge.git**
- Could also replicate results for several different face representation networks.
  - Doing it .
- Organize comparisons and documentation in LAtex maybe

# Organize the data

# Compare

1. **Dataset**
    - LFW
    - FRGC

2. **Face representation networks**
    - ArcFace  - angular margin
    - CosFace - cosene margin
    - SphereFace - multiplicative angular margin
    - FaceNet (triple loss) -distance based triplet margin
    - Dlib - euclidean embedding space

3. N**umber of imgs by identity**
    - All imgs
    - Filter min img
    - Filter 10-25, 10-15, 5-10 imgs

# Analyze

1. **Face representation networks**
    - Norm distributions
    - intra and inter class angular distribution
    - cluster compactation
    - Overlap between identities
    - Silhouette score / Davis-Bouldin
    - Implicit curvature of the embedding
    - Dimensionality effect 128 vs 512
    - Use t-sne vs UMAP vs PCA
    - Use AJD to state that it can reduce dimensionality

# Analyze

2. Analyze the stats from before
    - **Intrinsic dimension**
        - PCA
        - Instrinsic radius vs number of imgs - plot
        - Intrinsic dimension vs cluster dispersion - plot
        - Radius 2D
        - Radius 512D
        - Top 5 identities on smallest radius
        - Top 5 identities on largest radius
        - Radius vs dispersion plot

# Analyze

- **Visualize clusters**
  - Main direction global cluster

- **Distribution clusters individual and in general**
  - Radius 2d
  - Radius 512d
  - Cluster Dispersion
  - Top 5 on smallest dispersion
  - Top 5 on largest dispersion
  - Distribution individual cluster
  - Distribution general

- **Manifold**
  - Cosine similarity between centroids
  - Euclidean distance between centroids
  - Top 20 identities – number of imgs
  - Intrinsic dim vs cluster dispersion plot


GitHub

The-Bridge Public

Pin | Watch 0 | Fork 0 | Star 0

main | 1 Branch | 0 Tags | Go to file | Add file | Code

J0SEF4 Add README and update .gitignore (exclude large files) c9e8de6 · 1 minute ago 3 Commits

| | | |
|---|---|---|
| experiments | Initial clean commit without large CSV | 1 hour ago |
| stylegan2-ada-josefa | add stylegan2-ada-josefa | 54 minutes ago |
| .gitignore | Add README and update .gitignore (exclude large files) | 1 minute ago |
| README.md | Add README and update .gitignore (exclude large files) | 1 minute ago |

README

# Face Recognition Clustering and Illuimnation direction

This project contains experiments and analysis related to:

- StyleGAN2-ADA, focusing on face projection to latent space, synthetic image generation and illumination attribute direction.
- Facial clustering analysis, using FRGC and LFW dataset.

## Overview

The project is built on **StyleGAN2-ADA** (Adaptive Discriminator Augmentation), a generative adversarial network (GAN) architecture developed by NVIDIA that enables training high-quality generative models with limited datasets.

## About

*No description, website, or topics provided.*

Readme
Activity
**0** stars
**0** watching
**0** forks

## Releases

No releases published
Create a new release

## Packages

No packages published
Publish your first package

## Languages

**Jupyter Notebook** 99.2% **Other** 0.8%

## Suggested workflows

Based on your tech stack

**CMake based, multi-platform projects** Configure

# Sunday

25th January

# Analyze

1. **Face representation networks**
    - Norm distributions
    - intra and inter class angular distribution
    - cluster compactation
    - Overlap between identities
    - Silhouette score / Davis-Bouldin
    - Implicit curvature of the embedding
    - Dimensionality effect 128 vs 512
    - Use t-sne vs UMAP vs PCA
    - Use AJD to state that it can reduce dimensionality

# Monday

26th January

# Future Work

- Organize better documentation

# Thank You