2nd Week
The Bridge

StyleGan2-ADA
01/12 - 01/21

Josefa Fernández

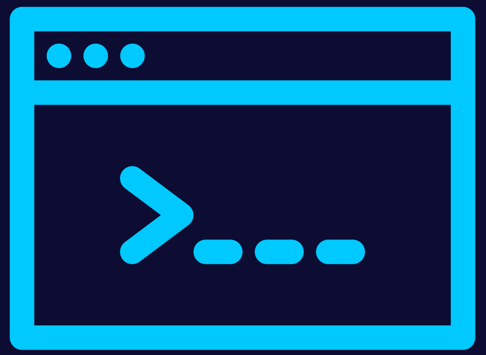
Monday ---- Tuesday

ToDo

- StyleGAN2-ADA
  - Generate new images.
  - Image Projection = find the latent vector who produce the image.

Terminal

1. **Enter Terminal CRC**
    - ssh jferna27@crcfe01.crc.nd.edu
2. **Connect SSH**
    - CRC conected to github.
3. **Docker**
    - used Docker with Singularity (did not have docker available)
3. **Remote SSH**
    - Open Command Palette (Ctrl+Shift+P) → Remote-SSH: Connect to Host...
    - Enter: jferna27@crcfe01.crc.nd.edu and password
4. **Add Dockerfile y docker_run.sh** (given by Prof.)
5. **Convert Dockerfile to Singularity**
    - singularity build --sandbox stylegan2_sif/ docker://nvcr.io/nvidia/pytorch:20.12-py3



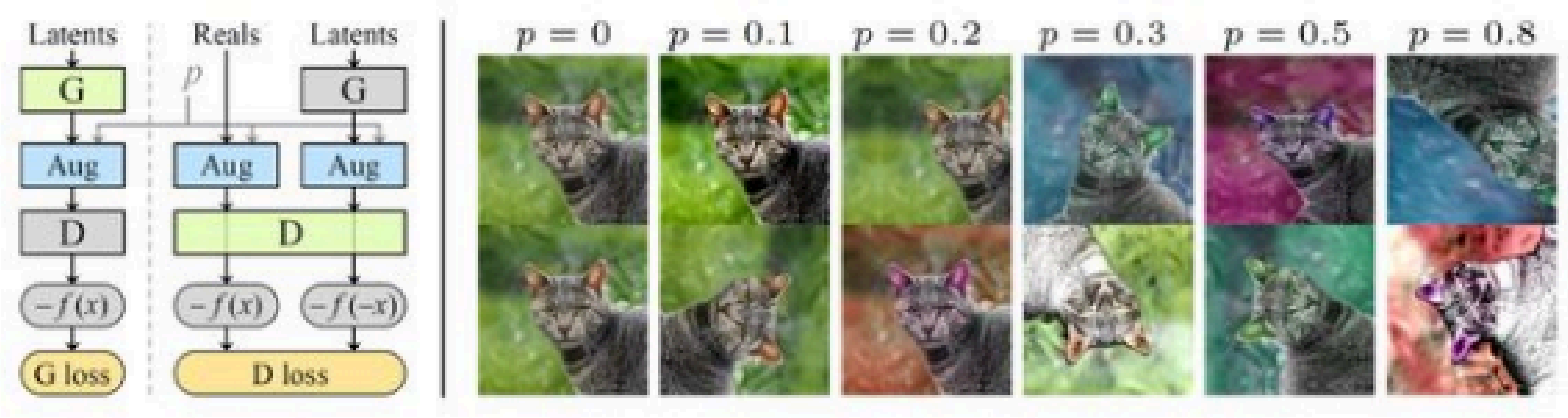
Error 1: Repository

- The command given is in StyleGAN2-ADA (Pytorch) (different repositories)

./docker_run.sh python3 generate.py --outdir=out --trunc=1 --seeds=85,265,297,849 --network=https://nvlabs-fi-cdn.nvidia.com/stylegan2-ada-pytorch/pretrained/metfaces.pkl

StyleGAN2	StyleGAN2-ADA
TensorFlow 1x	Pytorch
run_generator.py	generate.py
.pkl TF	.pkl PyTorch
Old Repo	New Repo

Right Repository



NVlabs/stylegan2-ada-pytorch: StyleGAN2-ADA - Official PyTorch implementation

StyleGAN2-ADA - Official PyTorch implementation. Contribute to NVlabs/stylegan2-ada-pytorch development by creating an account on GitHub.

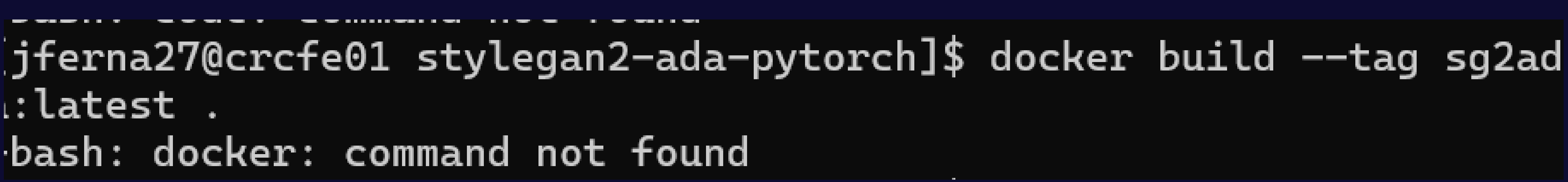
GitHub

https://github.com/NVlabs/stylegan2-ada-pytorch/tree/main

Error 2: Docker

I don´t have access to use Docker

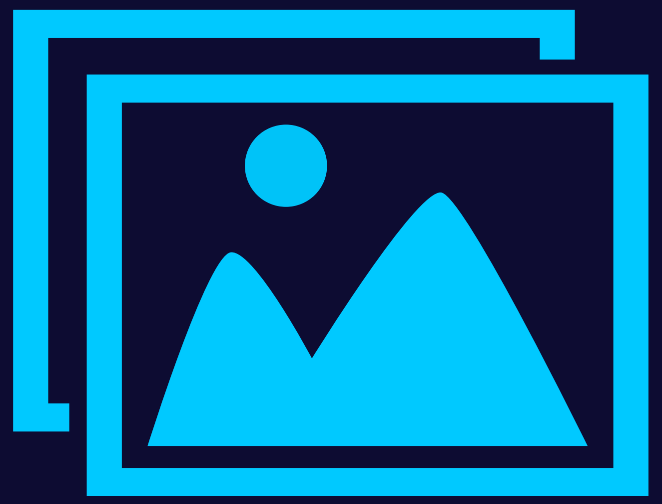
- Convert Dockerfile to Singularity
  - You can convert a Dockerfile or Docker image into a Singularity container and run it.
  - singularity build --sandbox stylegan2_sif/ docker://nvcr.io/nvidia/pytorch:20.12-py3
- Generate imgs with the pretraining
  - singularity exec --nv stylegan2_sif/ ./docker_run.sh python3 generate.py \
  - --outdir=out \
  - --trunc=1 \
  - --seeds=85,265,297,84 \
  - --network=https://nvlabs-fi-cdn.nvidia.com/stylegan2-ada-pytorch/pretrained/metfaces.pkl
- Don’t have access to GPU with singularity



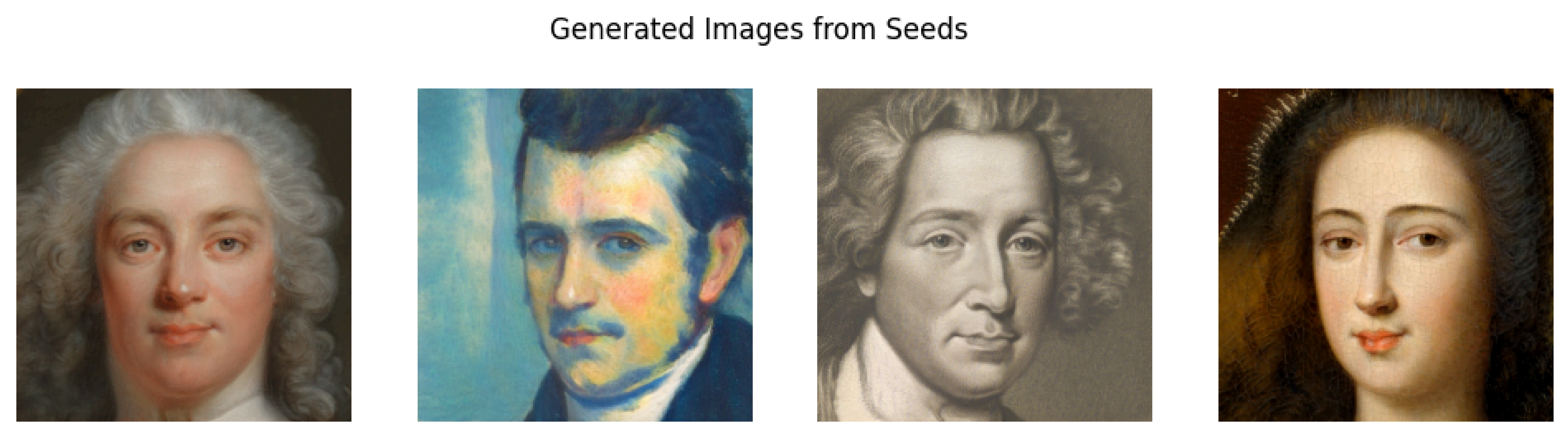
Temporal Solution

Use Google Colab

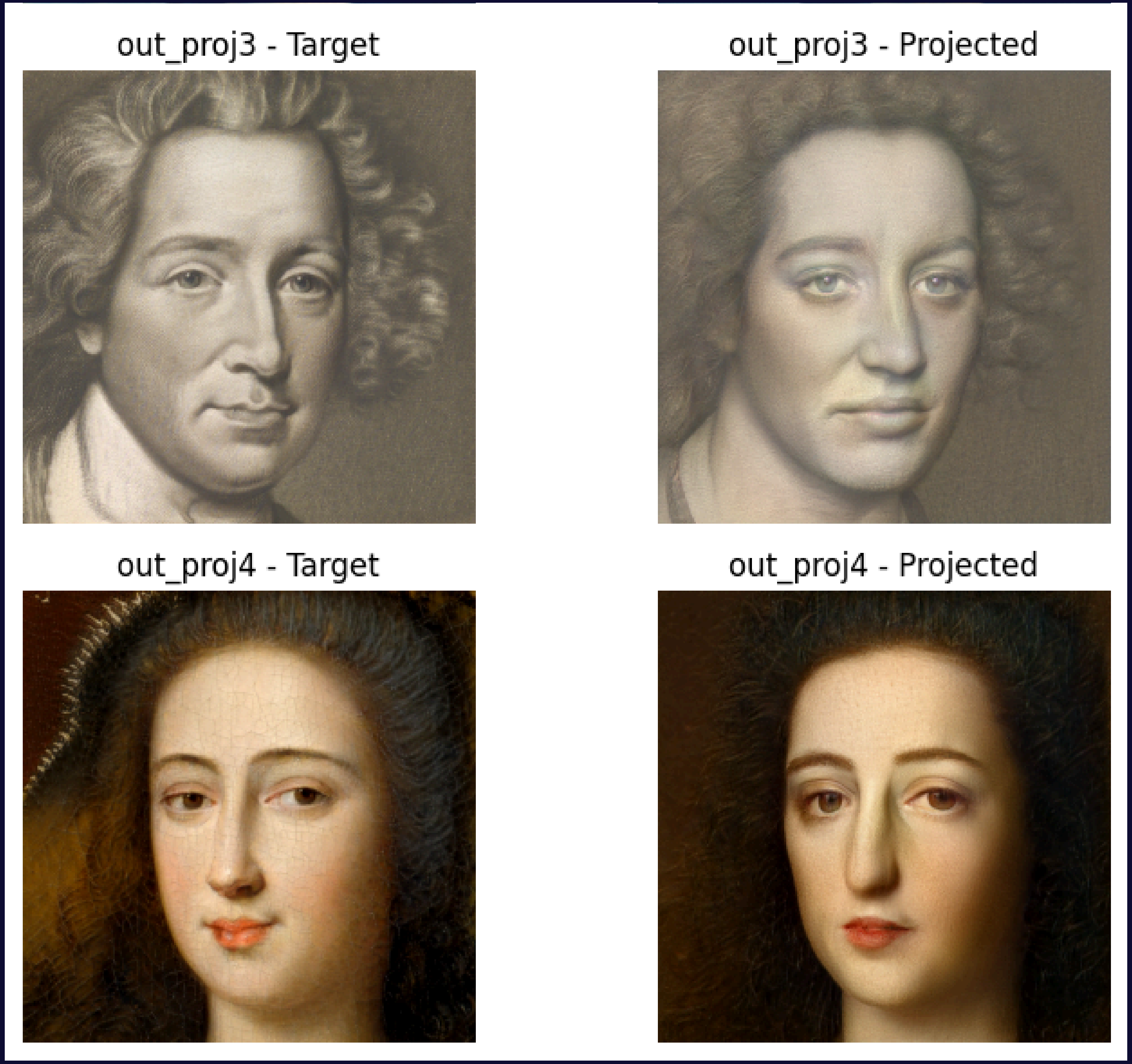
- Has GPU
- Generate
  - 4 images
- Projection
  - proj.png, target.png, projected_w.npz
- Render
  - proj00.png is the oficial img generated directly from de latent projected vector



1. Generate



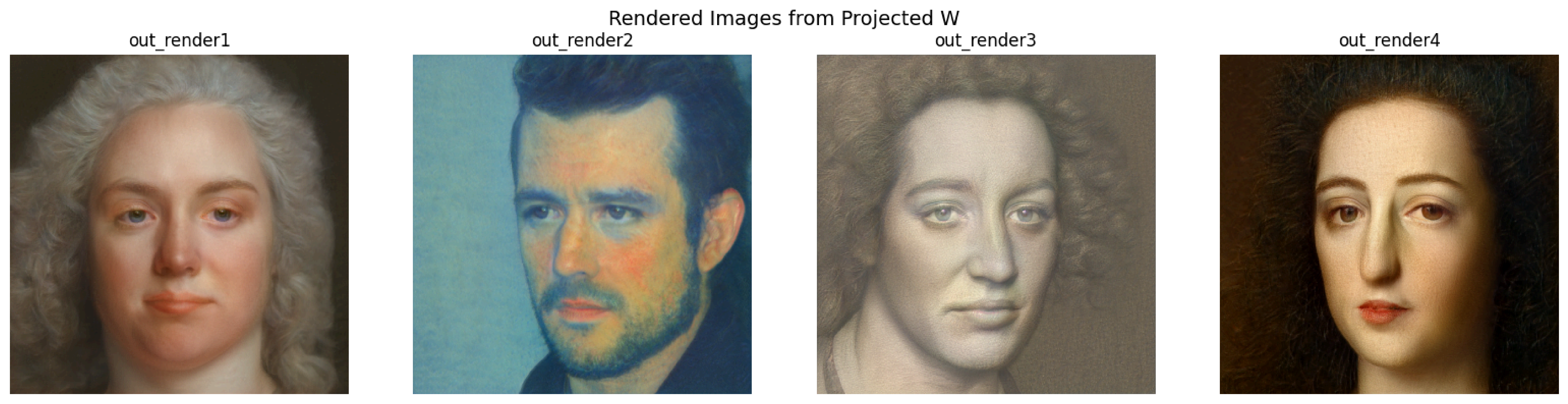
2.Projection



2.Projection

```
out_proj1: W shape = (1, 18, 512)
Values: [ 0.37795213  0.736854   -0.0468571  ...  0.53006405 -0.6227243
  0.602912  ]
-------------------------------------------------------------------------
out_proj2: W shape = (1, 18, 512)
Values: [ 1.4117142  -1.9028093  -0.11533726 ... -1.0594114  -2.3579
 -0.40707698]
-------------------------------------------------------------------------
out_proj3: W shape = (1, 18, 512)
Values: [ 0.94598705  1.5238333  -0.5994483  ... -1.2044903  -1.0617155
  2.7619157 ]
-------------------------------------------------------------------------
out_proj4: W shape = (1, 18, 512)
Values: [ 1.3914058   1.038446    1.6496087  ... -0.49879467 -0.32612914
  0.37301108]
-------------------------------------------------------------------------
```

3.Render from the projected vector



Wednesday ---- Monday

Desktop Computer & Analyze

Office

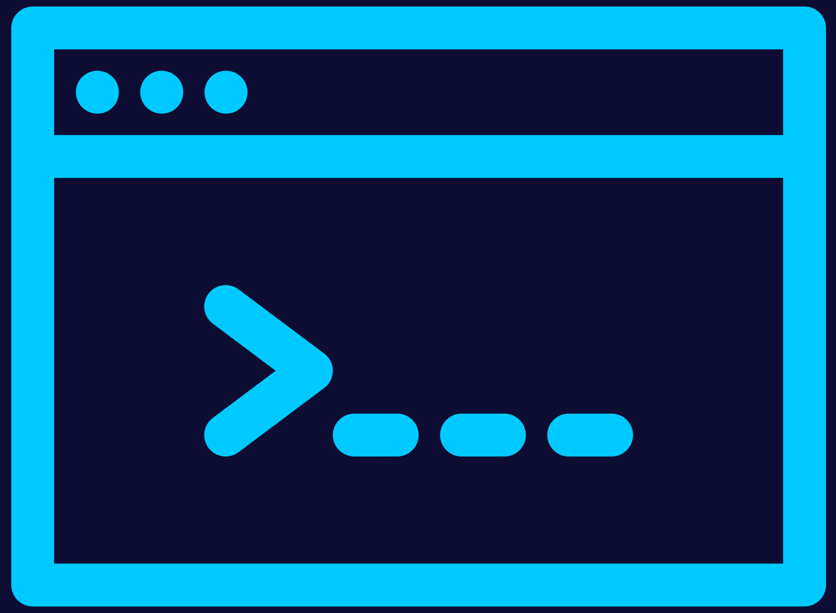
1. Access to the office
2. Password of the desktop computer
3. ssh jferna27@cvrl-flynn-ws4
    - Error is not available the **docker images**
4. ssh jferna27@cvrl-flynn-ws1
    - Error is not available **visual studio code** (need an authorization)
    - Then the **GUI** was not available
    - Tried to connect Remote - SSH VS Code, between 2 different computers (it was not possible)
    - Create an Github Repository (to use VS Code in my personal computer and the desktop computer to the terminal)
        - Generate
        - Projection

Office

1. Error uploading large files to github, the videos and the npz.
    - so i put these ones in the desktop computer.
2. **VS Code available in cvrl-flynn-ws4**
    - Use ws1 to use docker images (as a terminal)
    - Use ws4 to use VS Code
    - To use both use Remote - SSH
    - Generate / Projection / Render
    - Dont use anymore github

StyleGAN2-ADA

1. Generate
   - ./docker_run.sh python3 generate.py --outdir=out --trunc=1 --seeds=85,265,297,849 --network=https://nvlabs-fi-cdn.nvidia.com/stylegan2-ada-pytorch/pretrained/metfaces.pkl
2. Projection (change the out_proj2,3,4 and target the other imgs en out/)
   - ./docker_run.sh python3 projector.py --outdir=out_proj/out_proj1 --target=out/seed0085.png --network=https://nvlabs-fi-cdn.nvidia.com/stylegan2-ada-pytorch/pretrained/ffhq.pkl
3. Render
   - ./docker_run.sh python3 generate.py --outdir=out_render/out_render3 –projected-w=out_proj/out_proj3/projected_w.npz --network=https://nvlabs-fi-cdn.nvidia.com/stylegan2-ada-pytorch/pretrained/ffhq.pkl



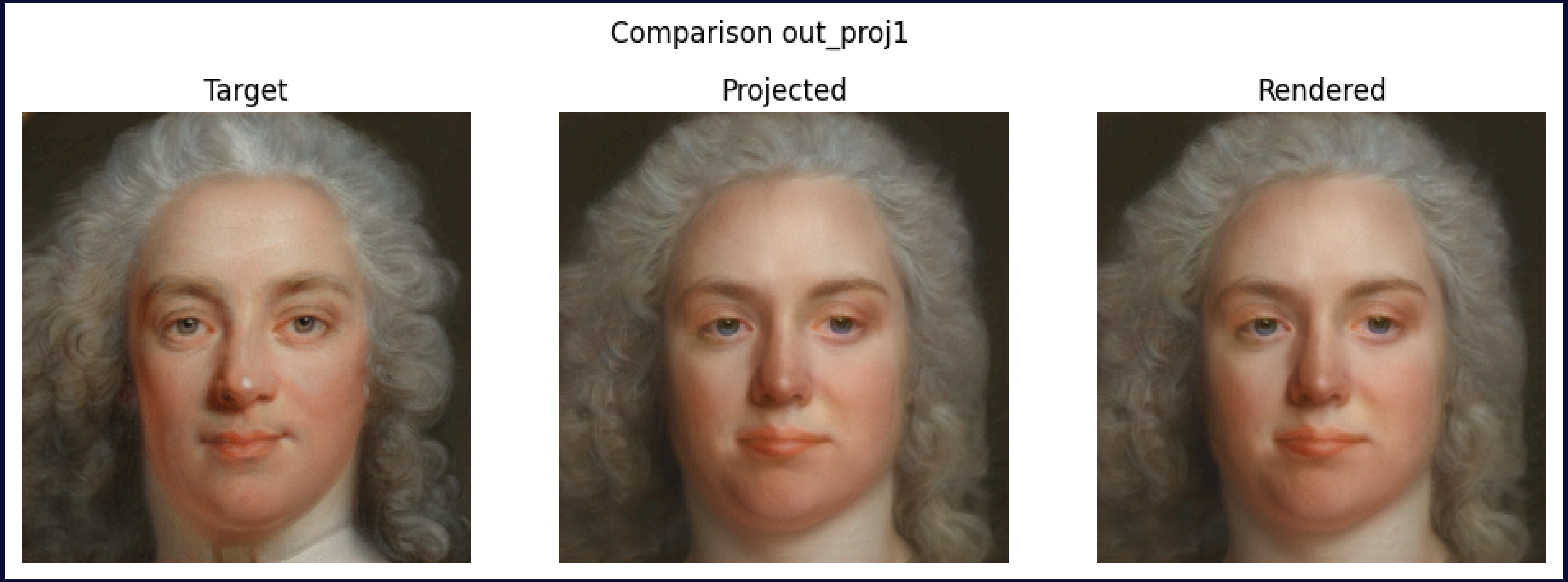
Analyze Target vs Proj vs Render

Projected vs Render vs Target

1. Use results of the generated imgs, projection and render
2. Load those imgs and turned it on RBG arrays
3. MSE between target/proj & target/render (measure pixel by pixel error)
4. SSIM between target/proj & targer/render (similarity)
5. latent vector “w” (projected_w.npz)
    a. shape
    b. mean
    c. std
    d. w[0] colormap (the 1st and only sample with shape (n layers, w dim)
        i. horizontal = dimensions W
        ii. vertical = layers
        iii. colors = magnitude
    e. Distribution of W values

out_proj1

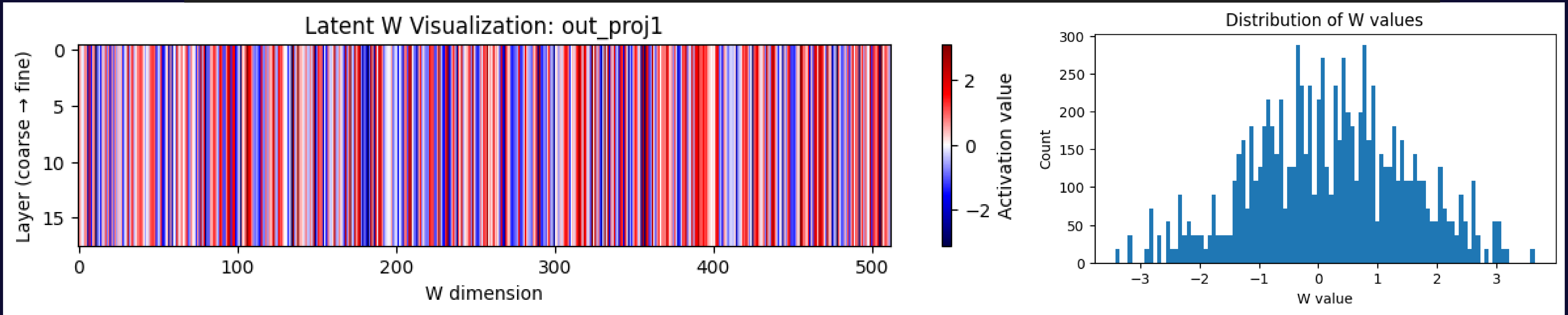
```
MSE Target vs Projected: 71.50
MSE Target vs Rendered: 71.77
SSIM Target vs Projected: 0.8177
SSIM Target vs Rendered: 0.8176
```



- MSE y SSIM low difference between them
- Render img reproduce almost the projected img

```
Vector W shape: (1, 18, 512), mean: 0.1861, std: 1.3046
```

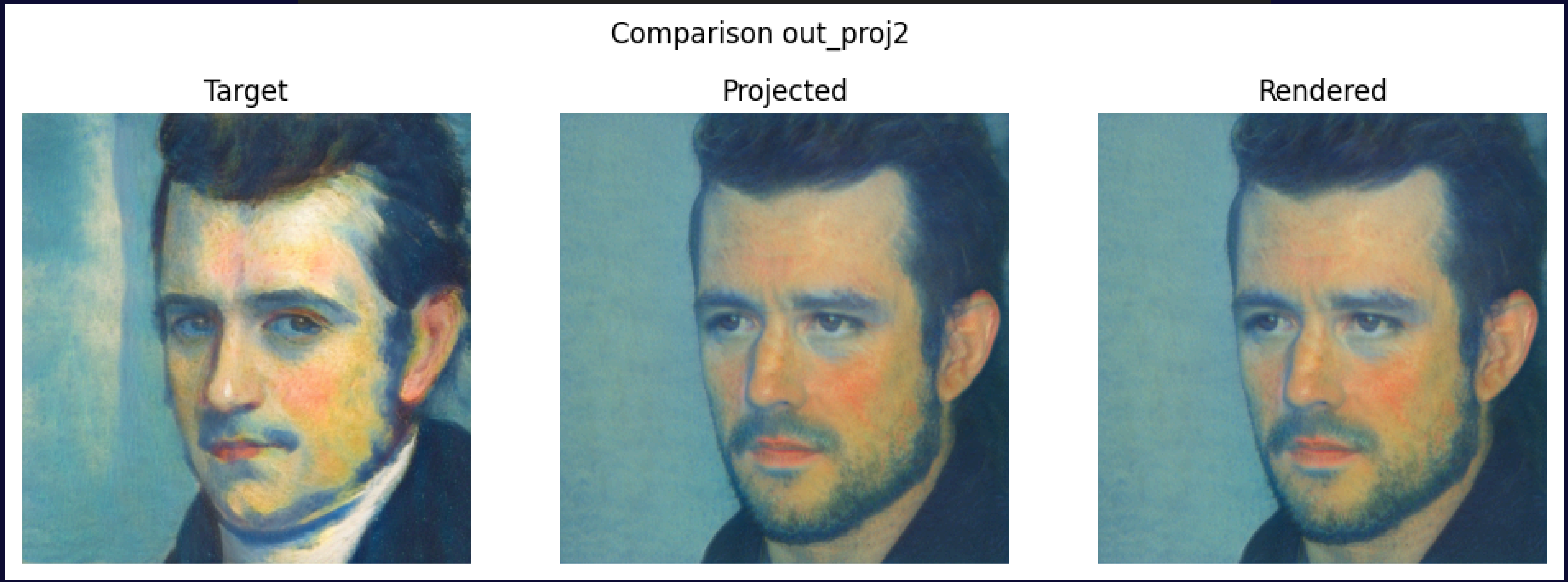
```
Per-layer mean: [0.186 0.186 0.186 0.186 0.186 0.186 0.186 0.186 0.186 0.186 0.186 0.186
 0.186 0.186 0.186 0.186 0.186 0.186]
Per-layer std : [1.305 1.305 1.305 1.305 1.305 1.305 1.305 1.305 1.305 1.305 1.305 1.305
 1.305 1.305 1.305 1.305 1.305 1.305]
```



- 1sample, 18 layers, 512 latent dimension per layer
- mean, close to vector is not displaced respect a tipic distribution
- std close to 1 normal, not so many variations
- per layer mean: little positive bias
- per layer std normal 1-1.5

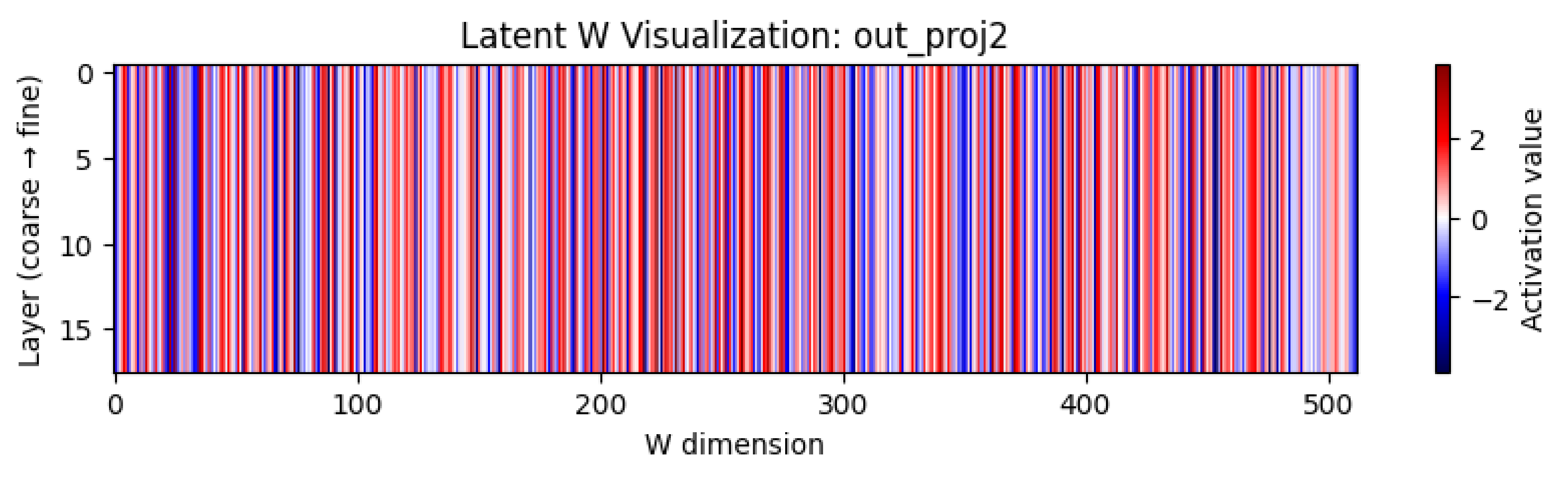
out_proj2

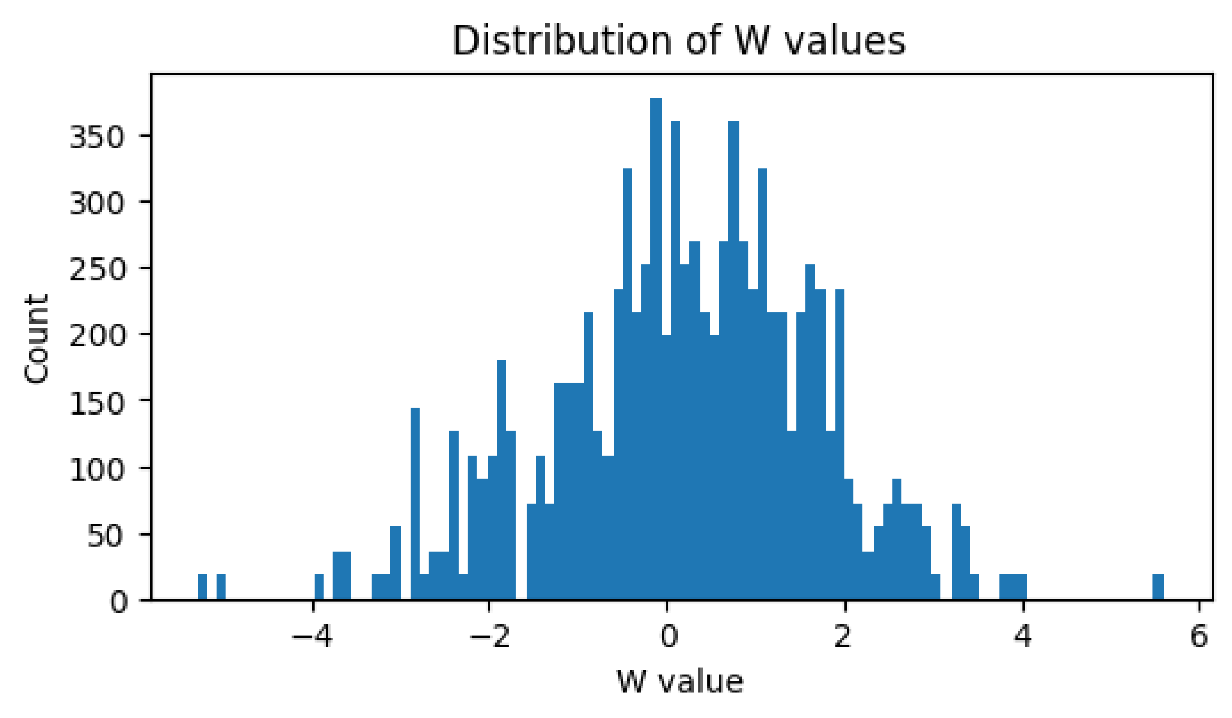
```
MSE Target vs Projected: 88.22
MSE Target vs Rendered: 88.22
SSIM Target vs Projected: 0.7224
SSIM Target vs Rendered: 0.7226
```



```
Vector W shape: (1, 18, 512), mean: 0.2024, std: 1.5244
```

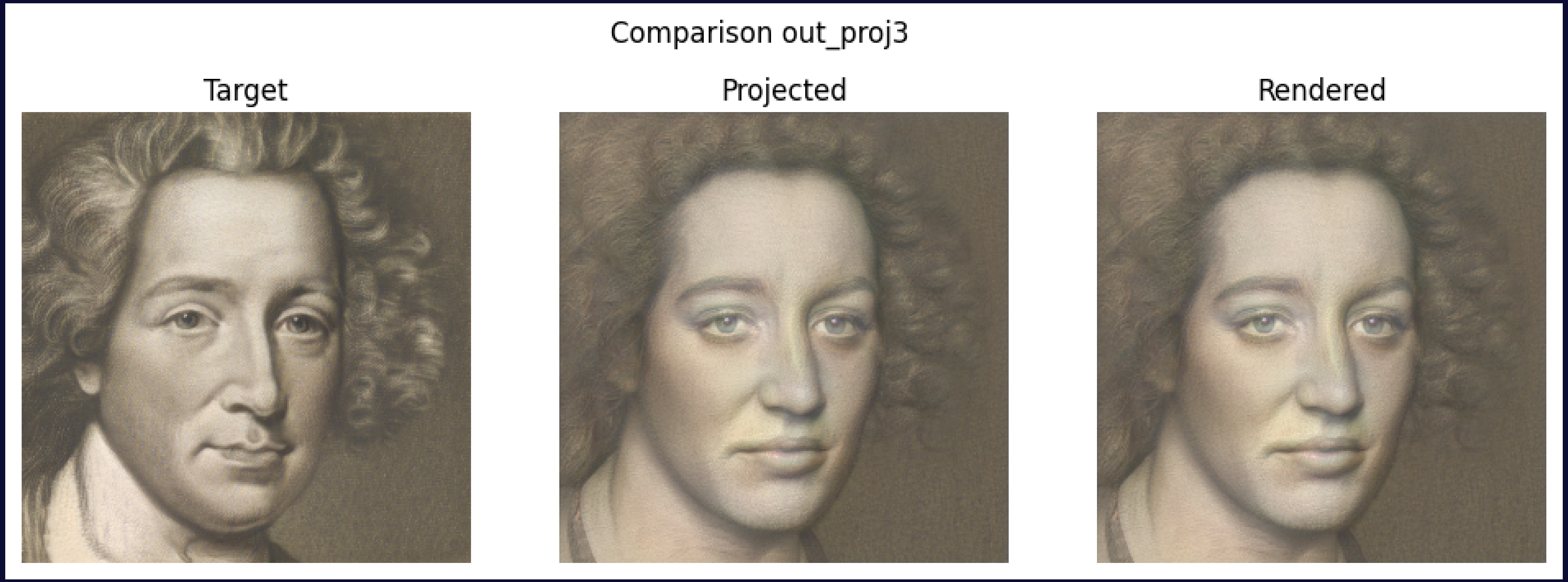
```
Per-layer mean: [0.202 0.202 0.202 0.202 0.202 0.202 0.202 0.202 0.202 0.202 0.202 0.202
 0.202 0.202 0.202 0.202 0.202 0.202]
Per-layer std : [1.524 1.524 1.524 1.524 1.524 1.524 1.524 1.524 1.524 1.524 1.524 1.524
 1.524 1.524 1.524 1.524 1.524 1.524]
```





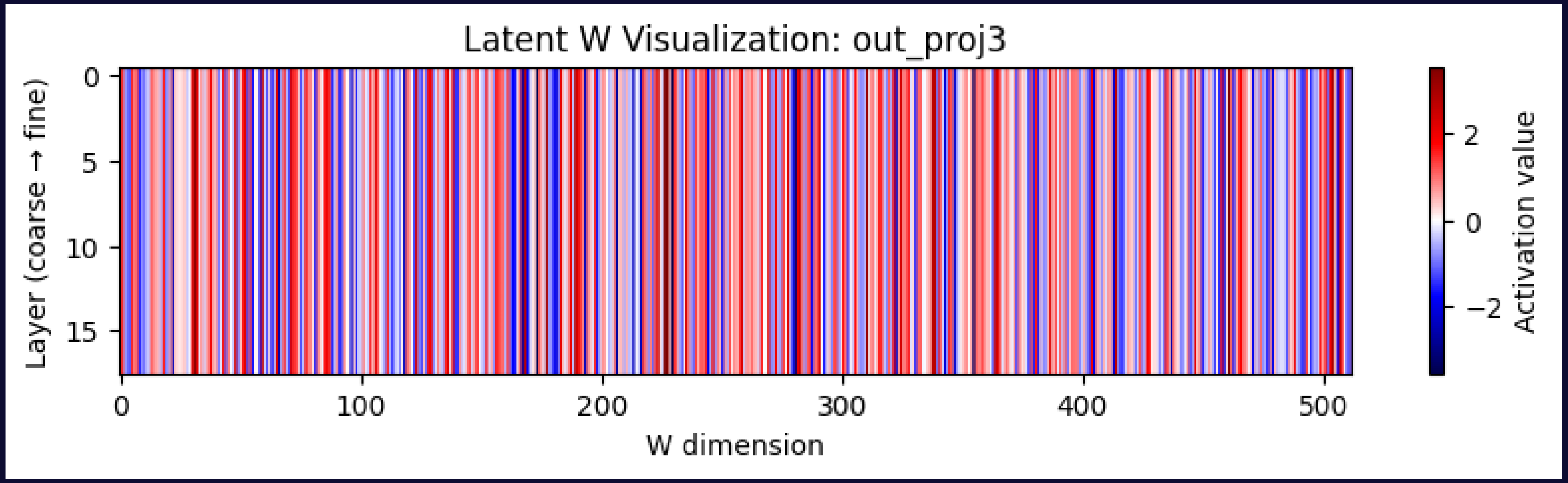
out_proj3

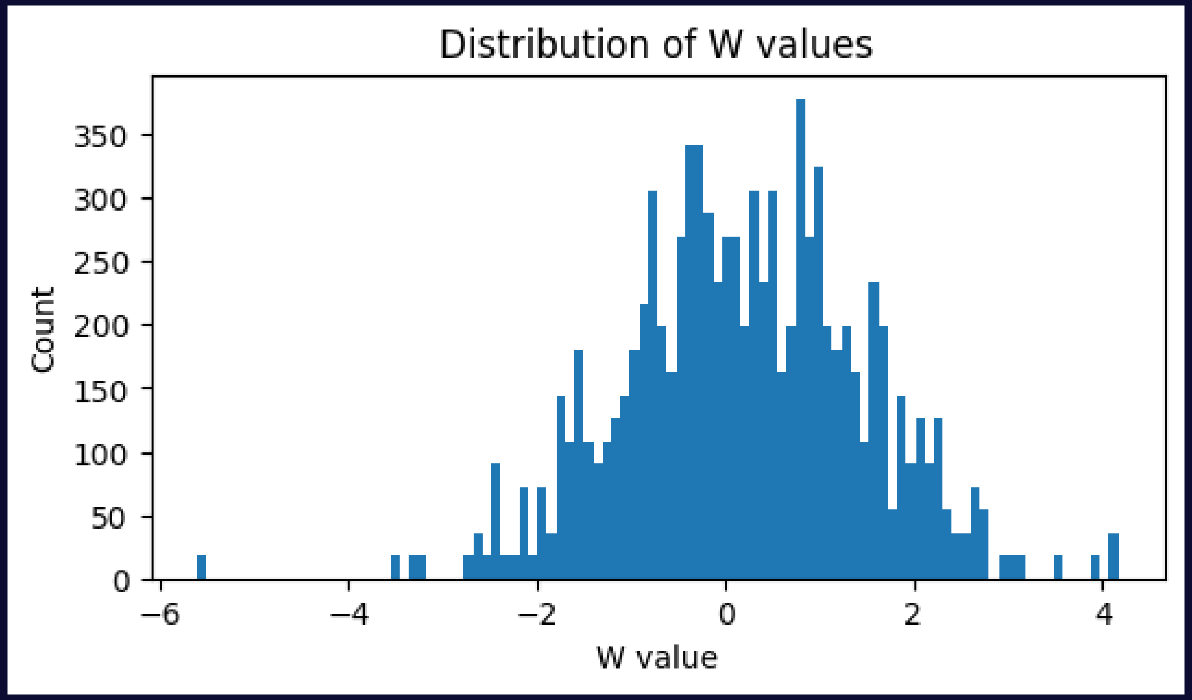
```
MSE Target vs Projected: 88.17
MSE Target vs Rendered: 88.37
SSIM Target vs Projected: 0.3732
SSIM Target vs Rendered: 0.3732
```



```
Vector W shape: (1, 18, 512), mean: 0.1982, std: 1.2823
```

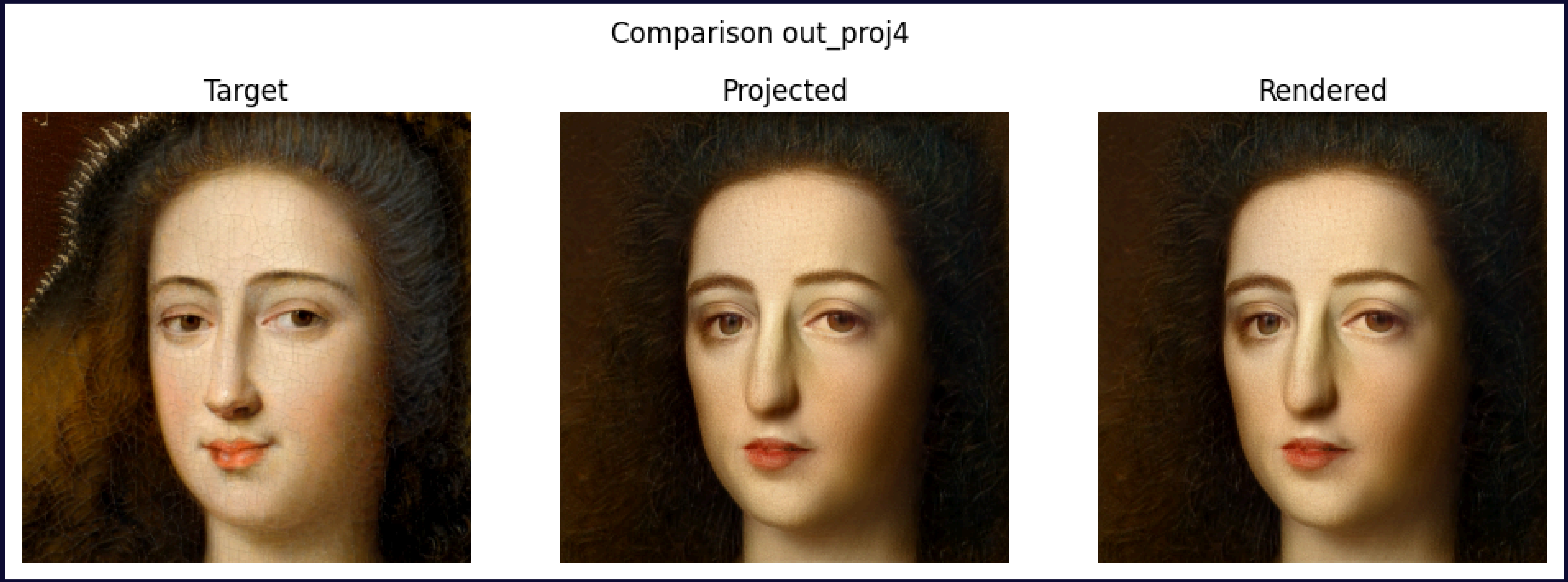
```
Per-layer mean: [0.198 0.198 0.198 0.198 0.198 0.198 0.198 0.198 0.198 0.198 0.198 0.198
 0.198 0.198 0.198 0.198 0.198 0.198]
Per-layer std : [1.282 1.282 1.282 1.282 1.282 1.282 1.282 1.282 1.282 1.282 1.282 1.282
 1.282 1.282 1.282 1.282 1.282 1.282]
```





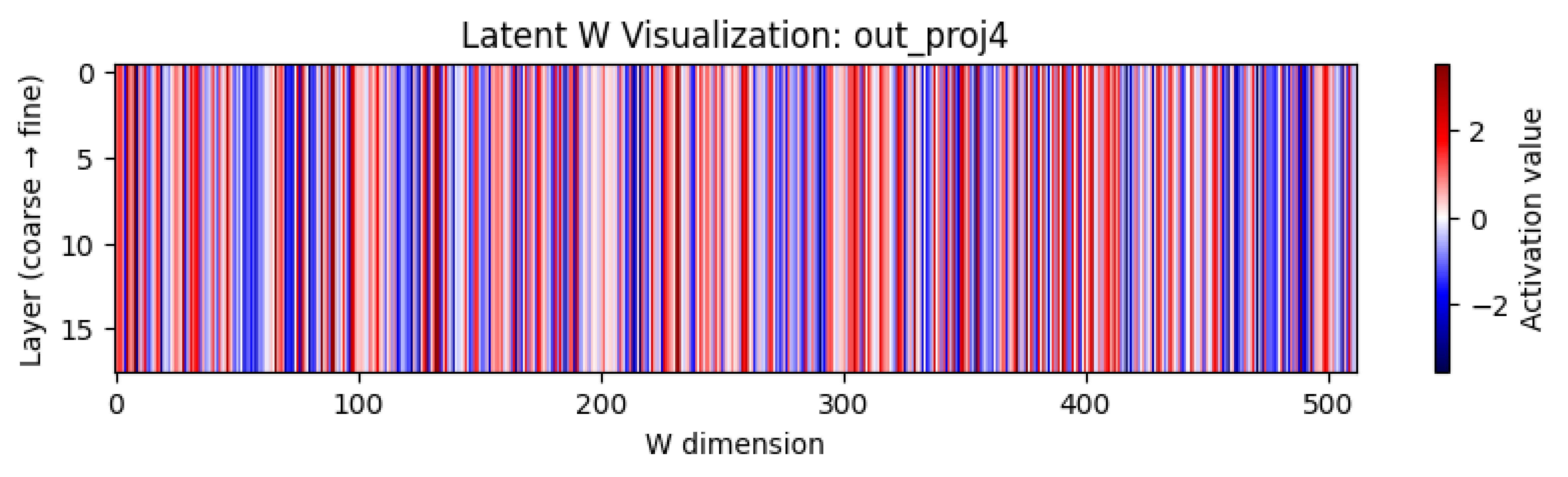
out_proj4

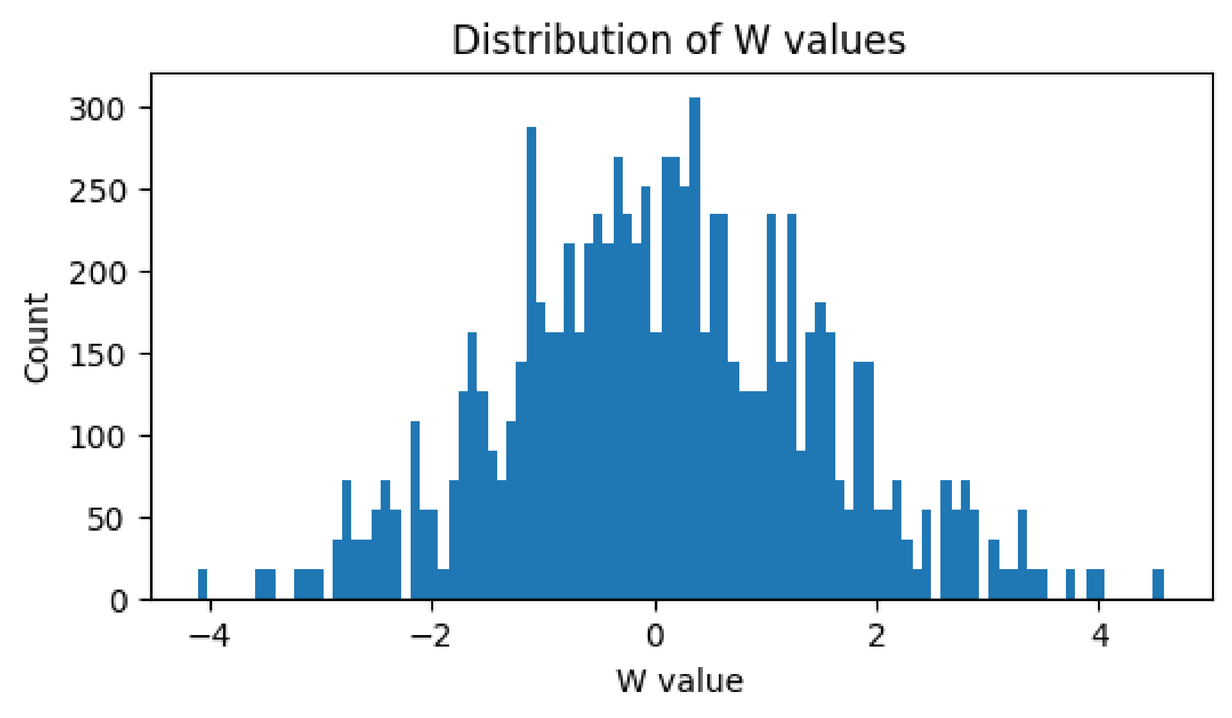
```
MSE Target vs Projected: 87.18
MSE Target vs Rendered: 87.02
SSIM Target vs Projected: 0.4523
SSIM Target vs Rendered: 0.4539
```



```
Vector W shape: (1, 18, 512), mean: 0.0925, std: 1.4058
```

```
Per-layer mean: [0.092 0.092 0.092 0.092 0.092 0.092 0.092 0.092 0.092 0.092 0.092 0.092
 0.092 0.092 0.092 0.092 0.092 0.092]
Per-layer std : [1.406 1.406 1.406 1.406 1.406 1.406 1.406 1.406 1.406 1.406 1.406 1.406
 1.406 1.406 1.406 1.406 1.406 1.406]
```

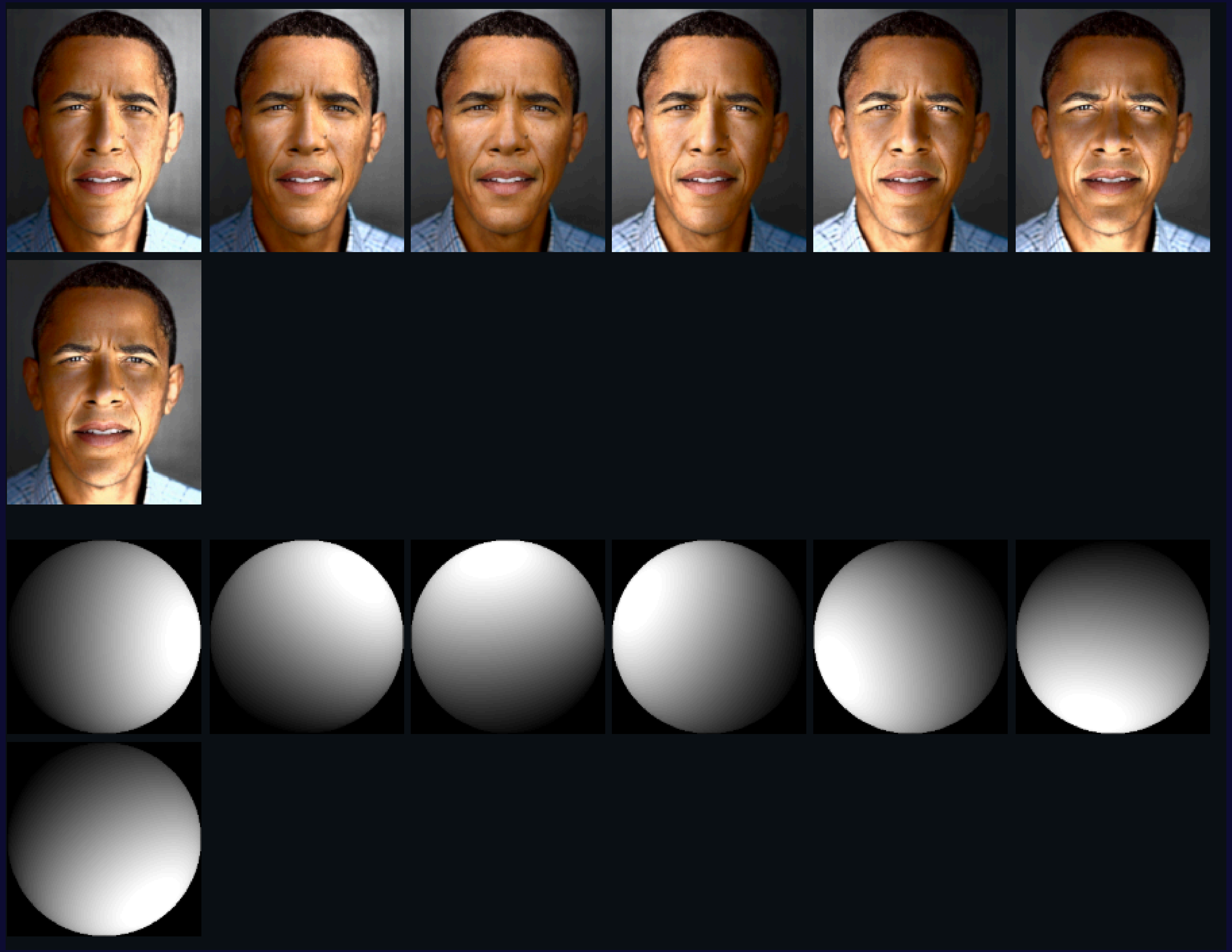




Interesting Papers

Deep Single-Image Portrait Relighting

- Change only the facial illumination
- Mantains the identity, pose and expression
- Use learned illumination maps
- https://github.com/zhhoper/DPR



For Illumination

Automated face recognition system for smart attendance application using convolutional neural networks

- The CNN was trained with dedicated database of 1890 faces with different illumination levels and rotate angles of total 30 targeted classes

- https://www.researchgate.net/publication/377268689_Automated_face_recognition_system_for_smart_attendance_application_using_convolutional_neural_networks

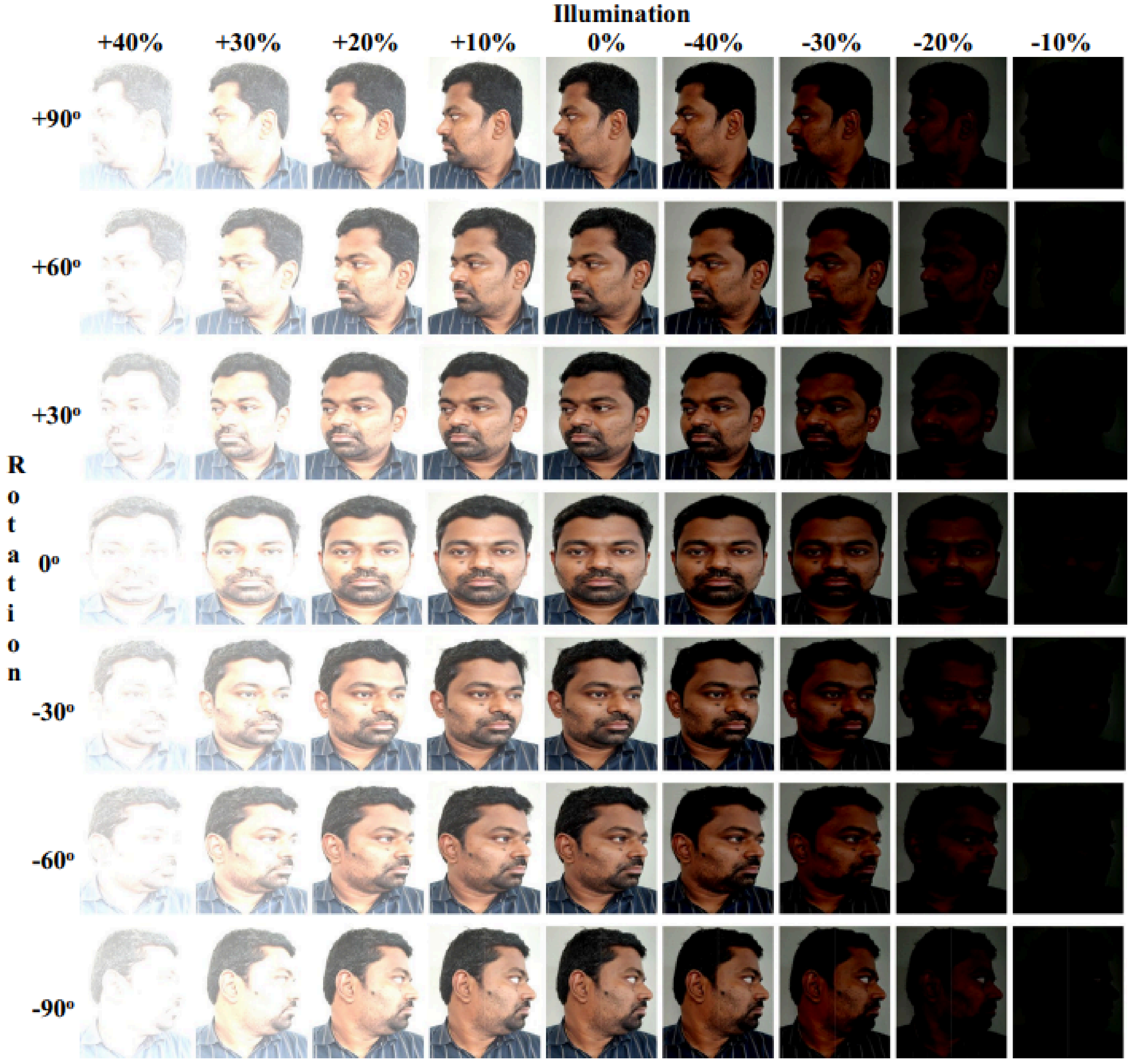
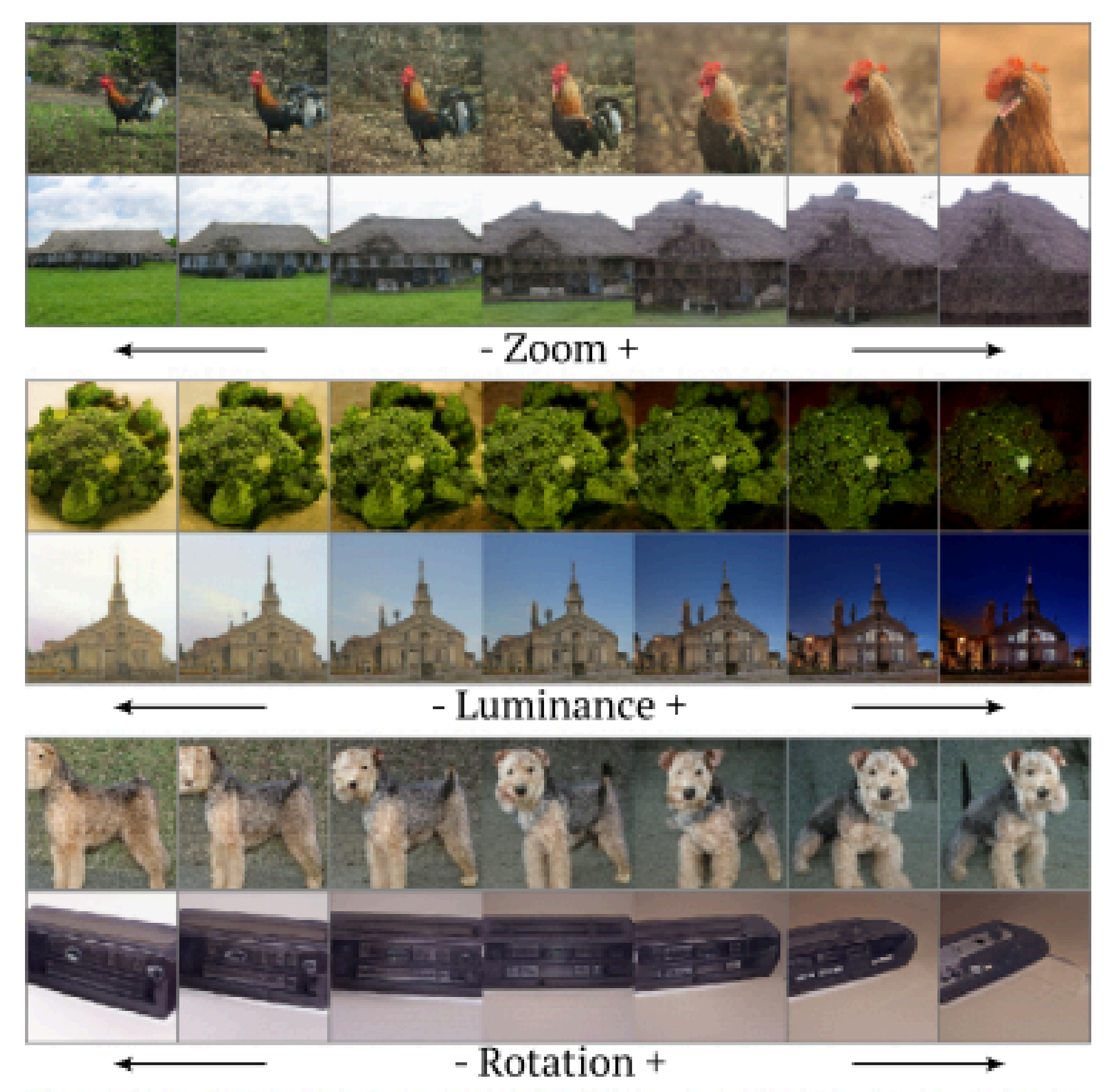


Fig. 3 Face database images with different illuminations and rotate angles

For normal Illumination & Rotation

Unsupervised Discovery of Interpretable Directions in the GAN Latent Space

- In this paper, we introduce an unsupervised method to identify interpretable directions in the latent space of a pretrained GAN model. The paper learns semantic directions by forcing a model to distinguish visual transformations, which aligns the latent space with independent real-world factors, without any kind of supervision.
- https://arxiv.org/pdf/2002.03754



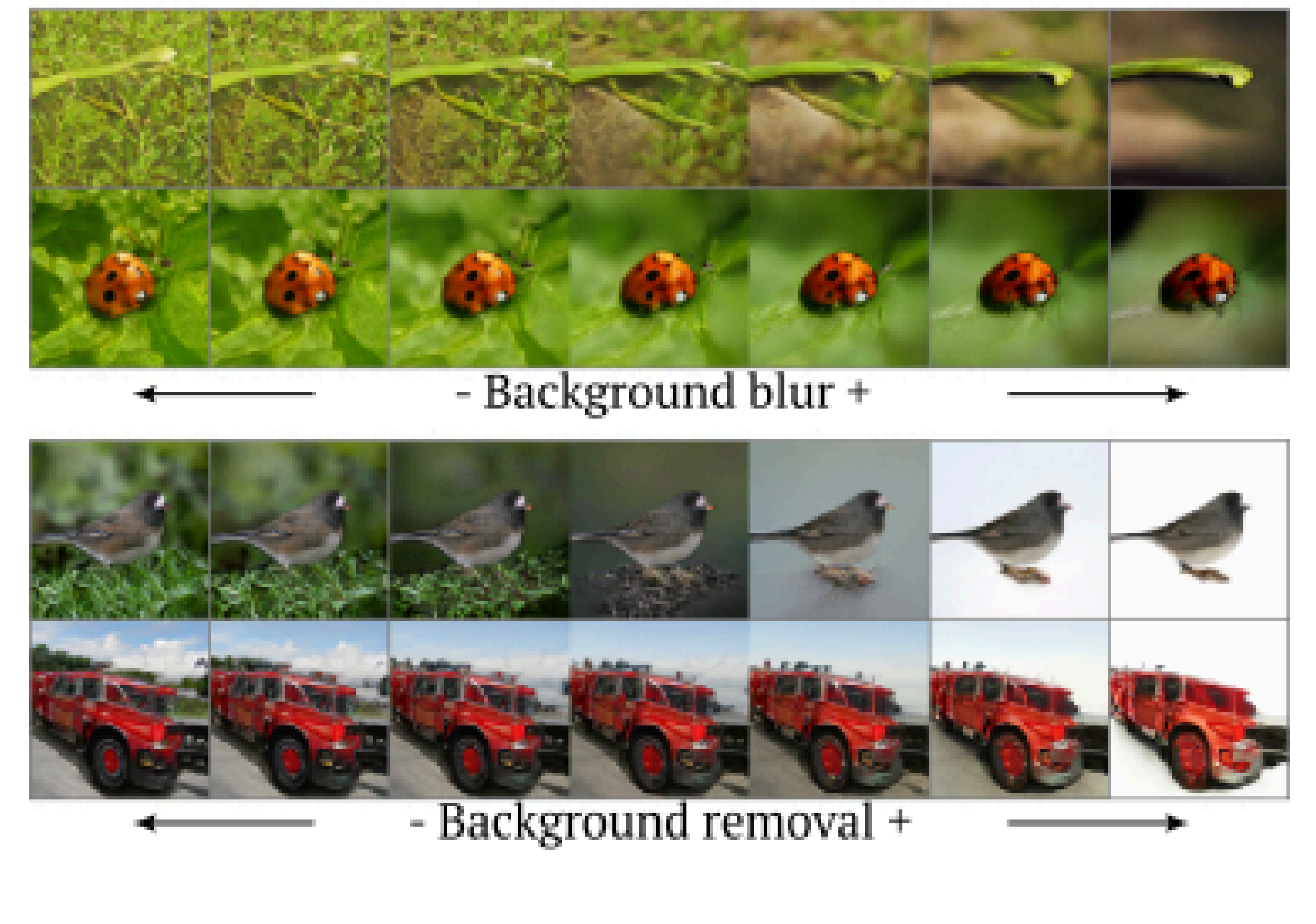


Figure 9. Examples of directions discovered for BigGAN.

InterFaceGAN: Interpreting the Disentangled Face Representation Learned by GANs

- InterFaceGAN identifies linear directions in a GAN's latent space that control facial attributes (age, gender, expression, glasses, pose), enabling precise and disentangled manipulation, even for real images through GAN inversion.
- https://arxiv.org/pdf/2005.09635

TABLE 1
Disentanglement analysis on PGGAN [1].

(a) Training data.

	Pose	Smile	Age	Gender	Glasses
Pose	1.00	-0.01	0.00	0.00	0.01
Smile		1.00	0.03	-0.09	-0.03
Age			1.00	0.20	0.15
Gender				1.00	0.19
Glasses					1.00

(b) Synthesized data.

	Pose	Smile	Age	Gender	Glasses
Pose	1.00	-0.01	-0.01	-0.02	0.00
Smile		1.00	0.02	-0.08	-0.01
Age			1.00	0.42	0.35
Gender				1.00	0.47
Glasses					1.00

(c) Semantic boundaries.

	Pose	Smile	Age	Gender	Glasses
Pose	1.00	-0.04	-0.06	-0.05	-0.04
Smile		1.00	0.04	-0.10	-0.05
Age			1.00	0.49	0.38
Gender				1.00	0.52
Glasses					1.00

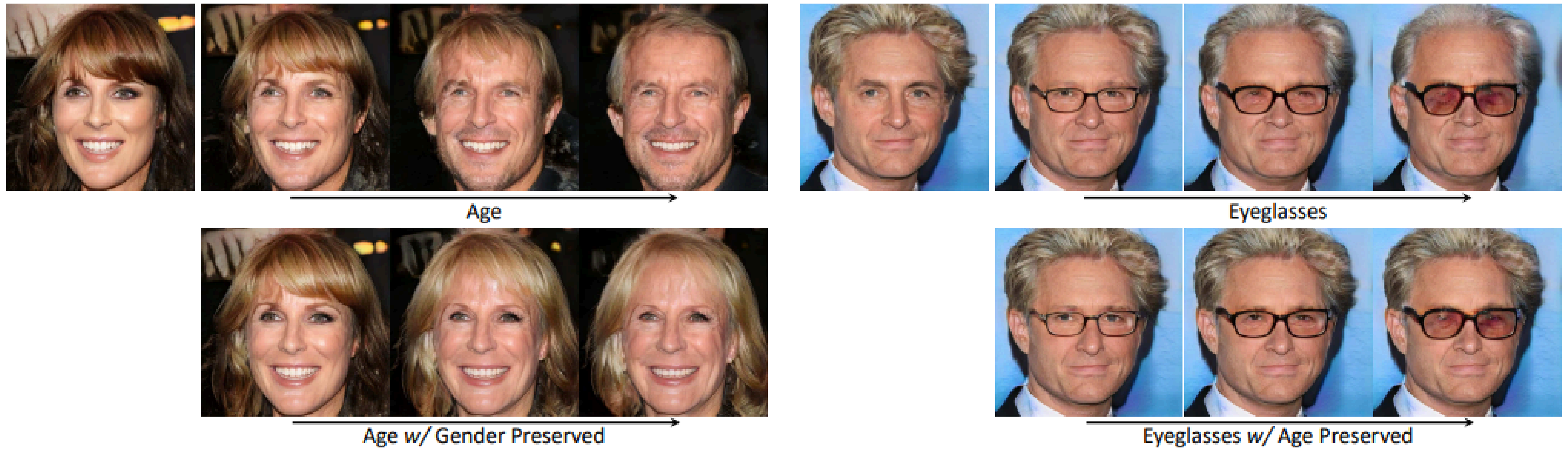


Fig. 9. **Conditional manipulation** results using PGGAN [1]. Left: Manipulating age attribute by preserving gender. Right: Manipulating eyeglasses attribute by preserving age. For each example, the top row shows the unconditional editing results while the bottom row shows the conditional manipulation.

Project Idea

Idea

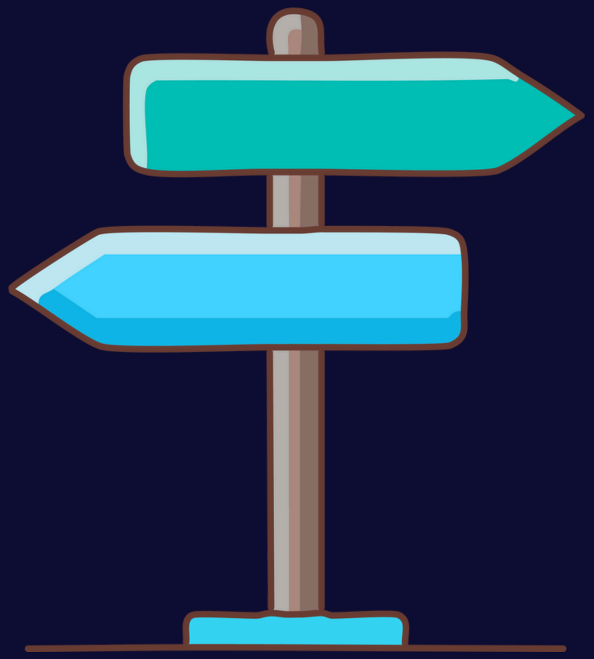
- Generate imgs with synthetic control of illumination in a generative model - GAN.
- Extract facial embeddings - Facenet.
- Measure if that non-attribute illumination corresponds to global consistent directions in the space of embeddings and if they are independent & orthogonal to the identity.

IDEA: quantified in discriminative embeddings how these directions correspond to controlled real-world variations in lighting.

Directional Structure of Non-Identity Attributes in Synthetic Face Embedding Spaces

Non-identitary attributes (illumination) corresponds to consistent directions in the facial embeddings space, approx. independent of the identity, when it is controled in a synthetic way?

- H1: Controlled changes in lighting induce shifts in embeddings that align in a consistent global direction.
- H2: The lighting directions are approximately orthogonal to the identity direction.



Idea

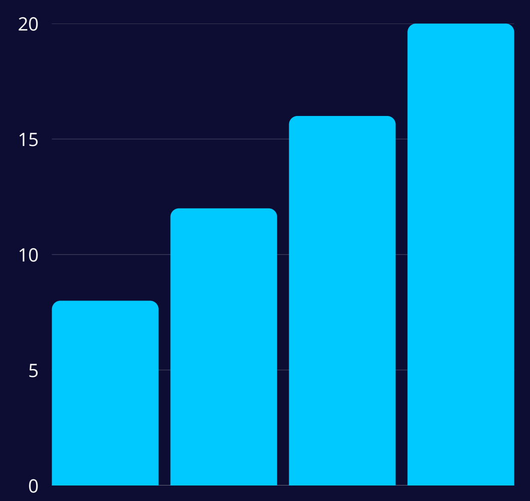
projection (StyleGAN2-ADA)
↓
synthetic img (controlled)
↓
detect face (MTCNN)
↓
embedding (Facenet)
↓
geometric analysis

Step by Step

1. Setup
2. Generate base identities
3. Obtain attribute direction (illumination)
4. Generation controlled synthetic
5. Extract embeddings
6. Embedding displacement
7. Directional consistency
8. Separation identity vs attribute
9. Visualizations
10. Alternatives

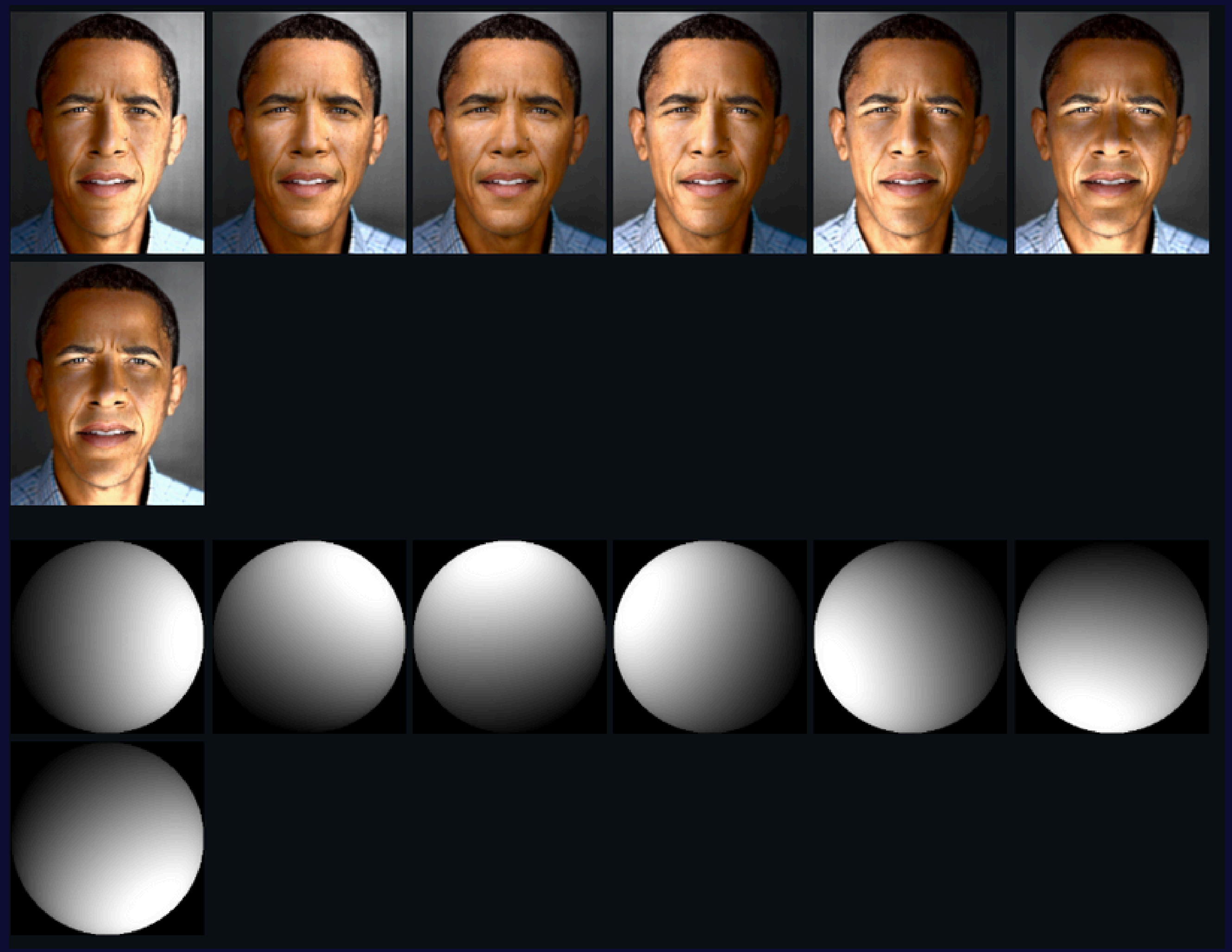
Setup

```
import sys
import os
import pickle
import torch
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.metrics.pairwise import cosine_similarity
from insightface.app import FaceAnalysis
from tqdm import tqdm
sys.path.append('/home/jferna27/project/stylegan2-ada-josefa')
import dnnlib
from PIL import Image
from facenet_pytorch import MTCNN, InceptionResnetV1
```



Generates Base Identities

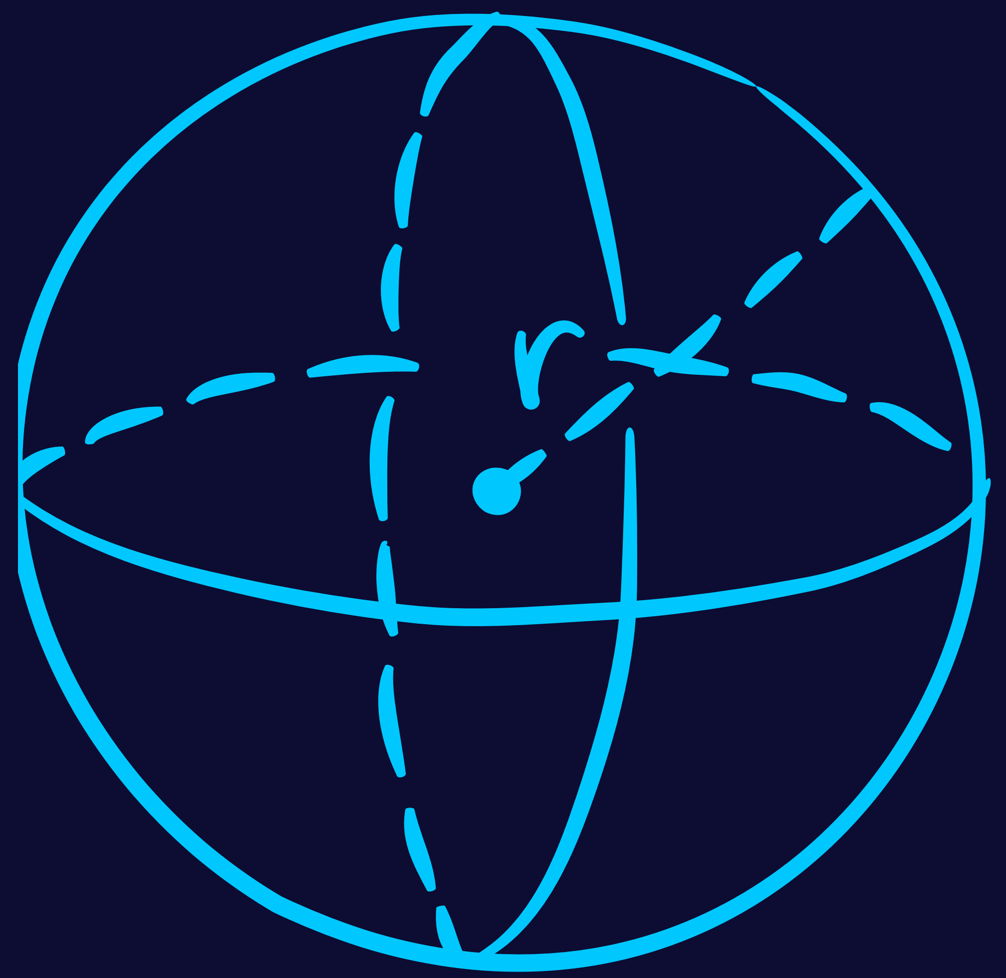
- Take the projection of face illumination Obama with StyleGAN2-ADA
- Load StyleGAN2-ADA
    - define GPU usage and the pretaines FFHQ generator
- Load Base Identities w0



Obtain Attribute Direction (illumination)

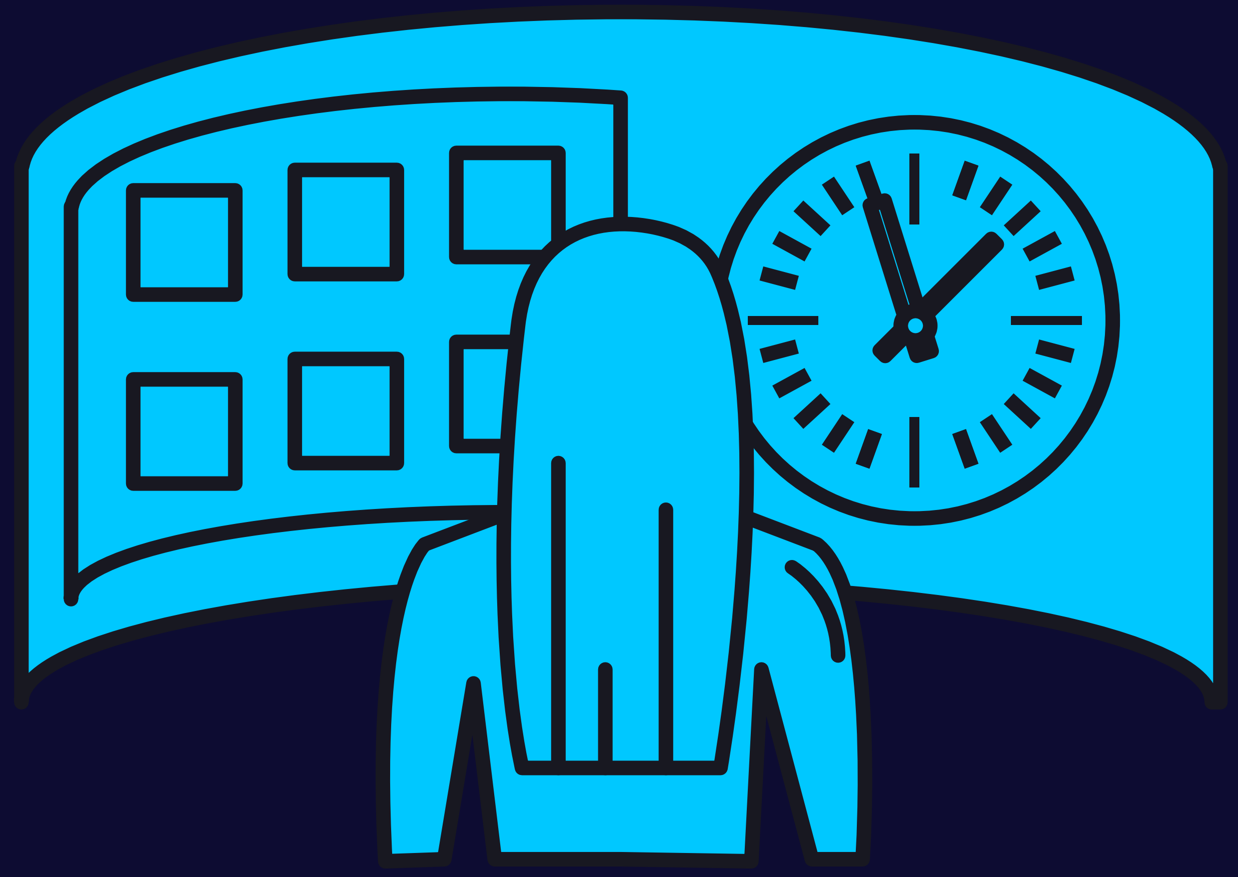
Use PCA in W-space to obtain global semantic directions

- Samples W for PCA
  - samples 2000 random latent vectors in Z space
- PCA
  - validate these visually: directions[x], then normalize
  - PCA finds the dominant variation directions in W
  - Selected PCA direction interpreted as lighting



Generation Controlled Synthetic

- Controlled Generator
  - generates imgs while varying only one attribute direction in this case the illumination
  - synthesizes the image



Extract Embeddings (ArcFace)

- Facial Embeddings
  - detects face - MCTNN
  - extract embeddings - FaceNet

```
Extracting embeddings from all generated images...
Embeddings: 100%|██████████| 49/49 [00:08<00:00,  6.04it/s]

Total embeddings extracted: 49
Imgs without detected faces: 0
```

Embedding Displacements

- Embedding Displacements
  - each vector measures how the embedding changes when the attribute changes

```
base_emb = {} #save baseline embeddings
for (i, alpha, emb) in embeddings:
    if alpha == 0:
        base_emb[i] = emb

deltas = [] #calculate normalized displacement
for (i, alpha, emb) in embeddings:
    if alpha != 0 and i in base_emb:
        d = emb - base_emb[i]
        d = d / np.linalg.norm(d)
        deltas.append(d)
```
✓ 0.0s

Directional Consistency

- Consistent Attribute Direction
  - normalize displacement
  - cosine similarity between all
  - produces a global attribute direction in embedding space
  - measures alignment between individual displacements and the mean direction

```
H1 (mean directional consistency): 0.042229373
```

H1: Controlled changes in lighting induce shifts in embeddings that align in a consistent global direction

- H1 dont supported, the illumination dont form a unique direction in the embedding space, but it is close to 0 to say there are perpendicular without directional relation (it has to be =1 to both deltas points out in the same direction)

Separation Identity vs Attribute

- Orthogonality
  - defines an identity direction
  - near 0: attribute independent of identity (H2 check)
  - large magnitude: attribute entangled with identity

```
Identity vs Illumination cosine: 0.044242173
```

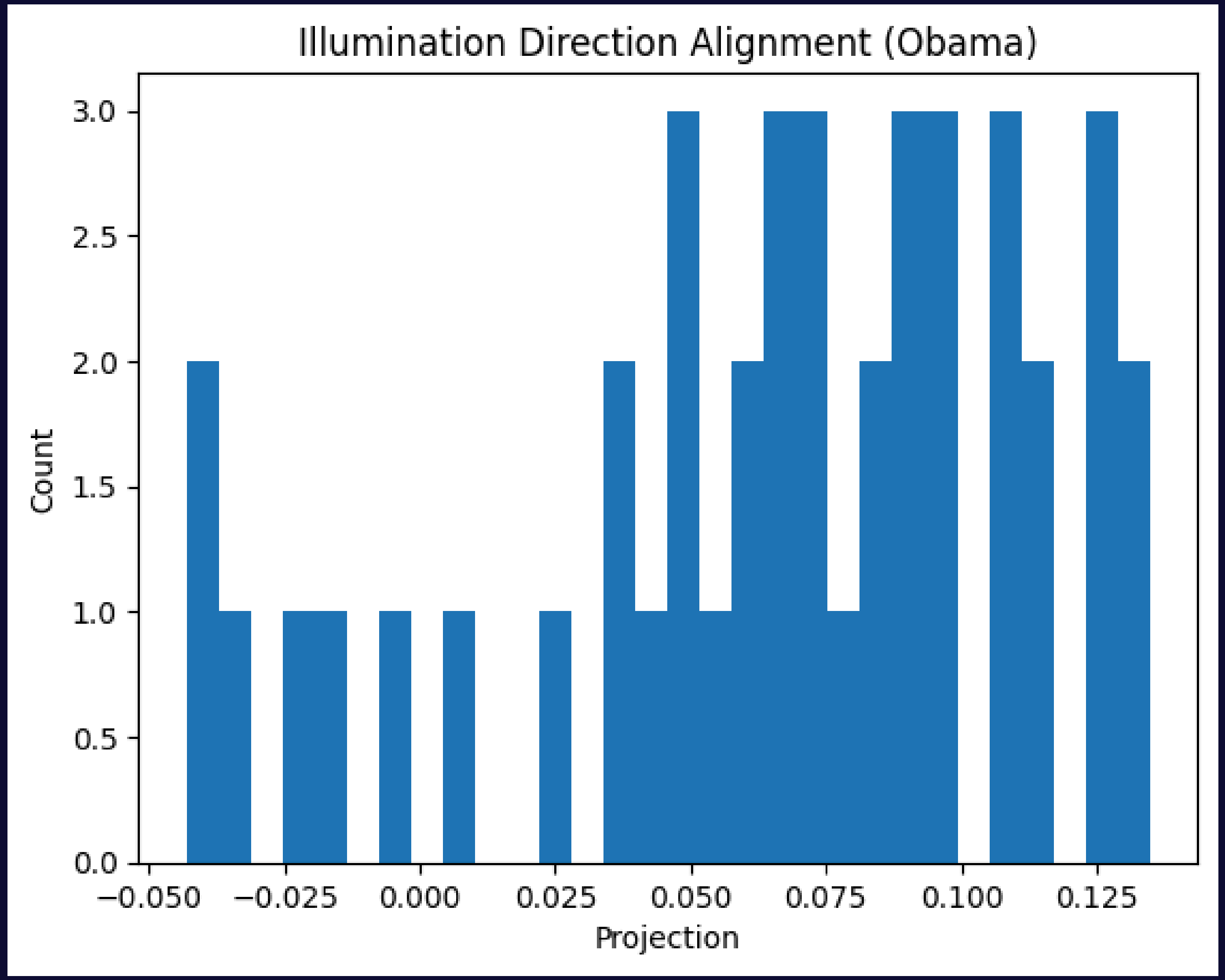
H2: The lighting directions are approximately orthogonal to the identity direction.

- H2 supported identity and illumination are orthogonals. independents

Visualizations

1. Illumination Direction Alignment

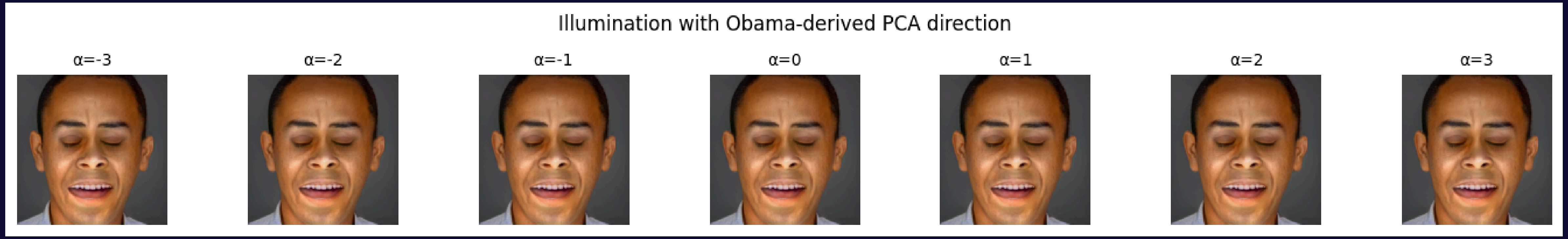
- Analyze alignment of embedding displacements with average illumination direction
- See how in every change the illumination points out, in the same direction in the embedding space
- Projection = delta · illumination_direction (delta = embedding change vector)
- Count: Number of displacements falling within each projection range
- projections range from -0.05 to 0.125 with no dominant peak (H1 = 0)
- No consistent directional alignment



Extract illumination direction form real obama projections

```
Explained variance ratio (Obama PCA): [3.4965709e-01 2.0007437e-01 1.4076298e-01 1.3227582e-01 9.1953561e-02
 8.5276179e-02 4.2211373e-13]
First component explains 35.0% of variance
illumination direction: tensor([[[[-0.0185,  0.0105,  0.0015,  ..., -0.0111,  0.0269,  0.0110],
          [-0.0185,  0.0105,  0.0015,  ..., -0.0111,  0.0269,  0.0110],
          [-0.0185,  0.0105,  0.0015,  ..., -0.0111,  0.0269,  0.0110],
          ...,
          [-0.0185,  0.0105,  0.0015,  ..., -0.0111,  0.0269,  0.0110],
          [-0.0185,  0.0105,  0.0015,  ..., -0.0111,  0.0269,  0.0110],
          [-0.0185,  0.0105,  0.0015,  ..., -0.0111,  0.0269,  0.0110]]],
        device='cuda:0')
```

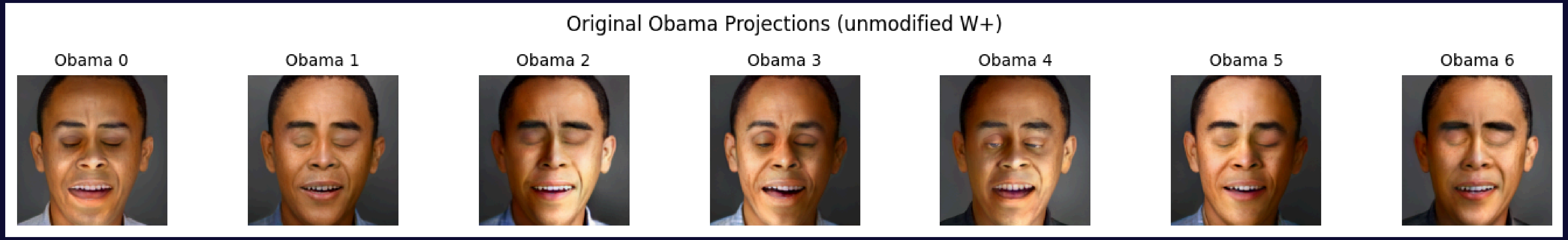
Regenerate imgs with Obama derived illumination direction



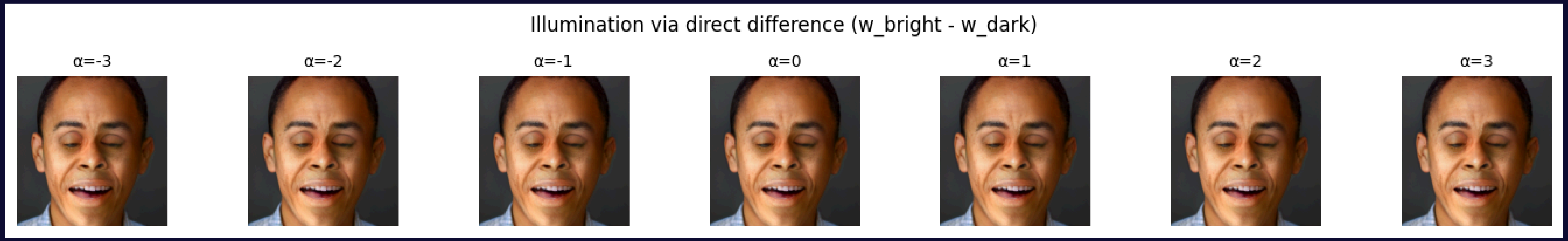
Even with Obama derived PCA, no illumination changes are visible.

Synthetize original Obama Projections

- synthesize the original Obama projections (without averaging) to verify real illumination differences exist.
- its ok



Use Direct Difference Between 2 obama projections



- Instead of PCA -> direct vector difference between the brightest and darkest Obama projections as illumination direction
- Maybe the problem is that I use the img obama 3 as the base identity, and this one also have changes of illumination and is similar to the others

Extract embeddings from original obama projections

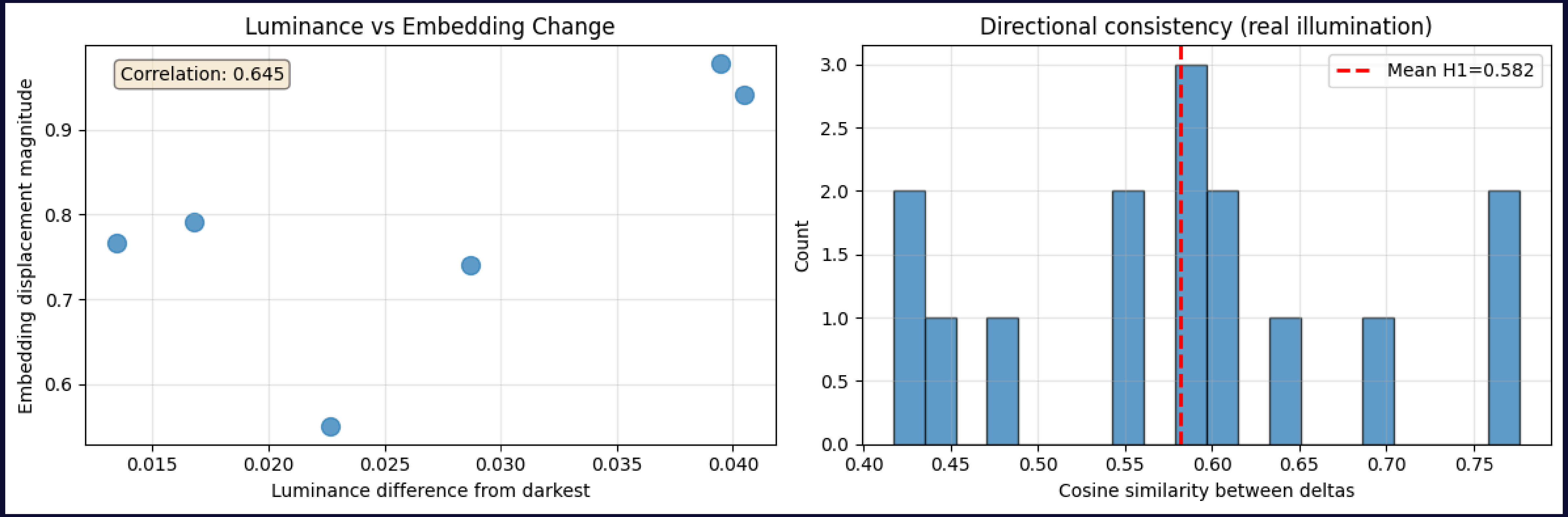
Calculate Luminance = 0.299*R + 0.587*G + 0.114*B and get the mean of them.
From: https://www.sciencedirect.com/topics/computer-science/luminance-component

Analyze correlation between luminance and embedding displacement

```
H1 (mean directional illumination consistency): 0.5818559527397156
```

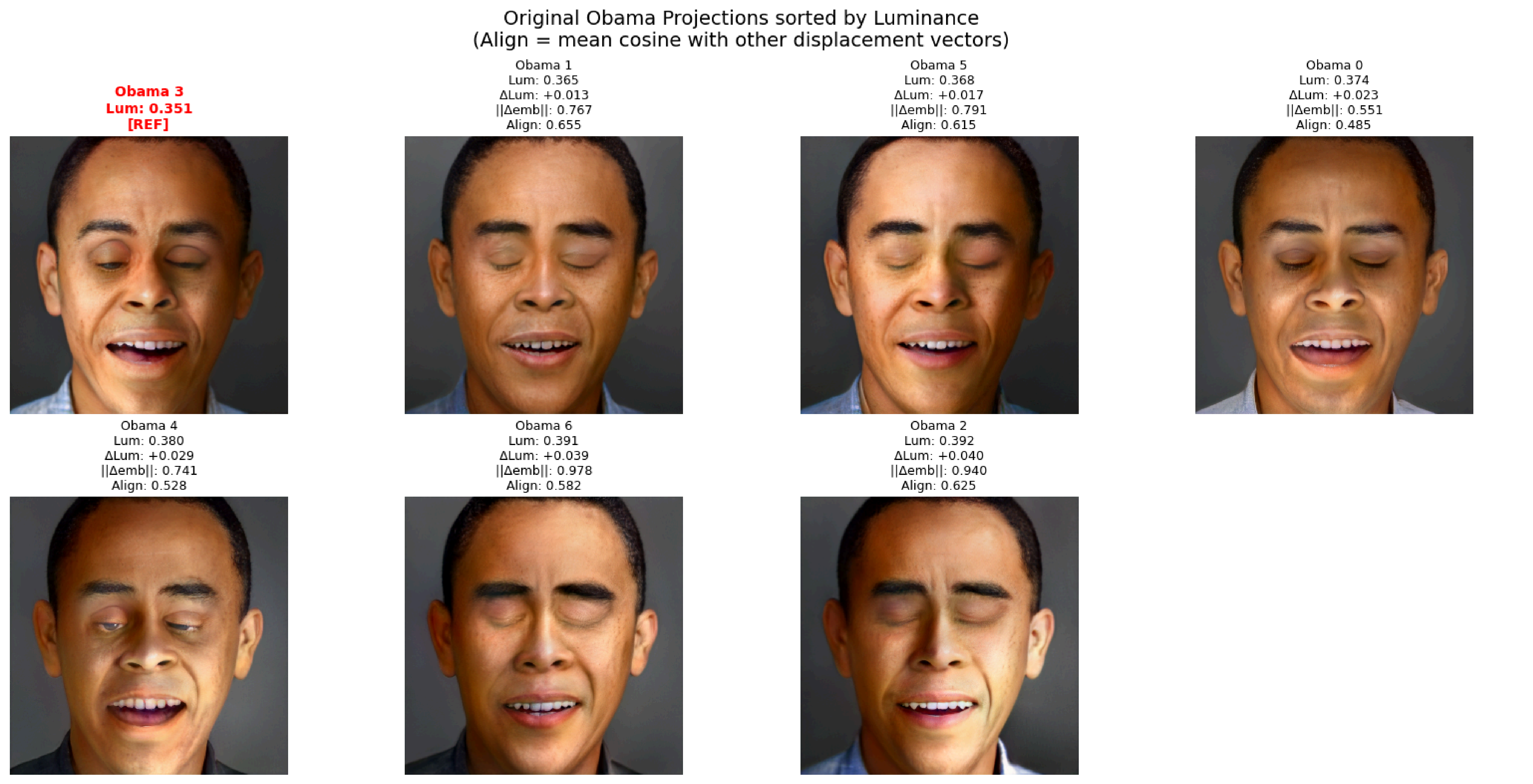
It forms a consistent direction in embedding space, but it could be better

Luminance vs embedding displacement magnitude



Imgs + Luminance values + Displacement Info

- Lum = diff of luminance
- Emb = how diff is the embedding between actual img and reference img
- Align = average cosine similarity between that img embedding change and the embedding changes of the other imgs, how much it points in the same direction as the rest. (close to 1, the best)



Conclusion

- Illumination is NOT linearly encoded in StyleGAN2-ADA W+ latent space
- All attempts to gnerate illumination variations via linear W+ manipulation failed
    - Random PCA
    - Obama specific PCA
    - DIrect difference

Alternative Data: This person does not exist

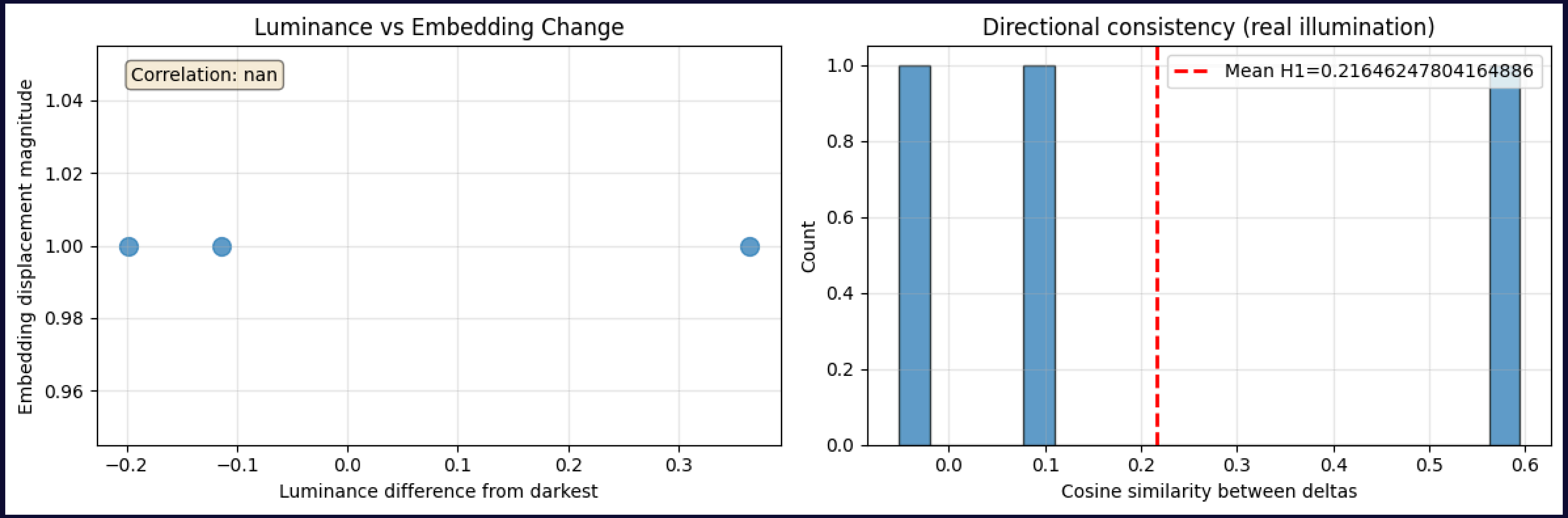
Methodology

1. Setup
2. Load StyleGAN2-ADA
3. Projections from the new imgs
4. Load projections
5. Detect face + extract embeddings
6. H1 directional consistency in the embeddings by illumination
    a. Embedding Displacements
    b. Directional Consistency H1
7. Luminance vs displacement
8. Order by luminance and info

Results

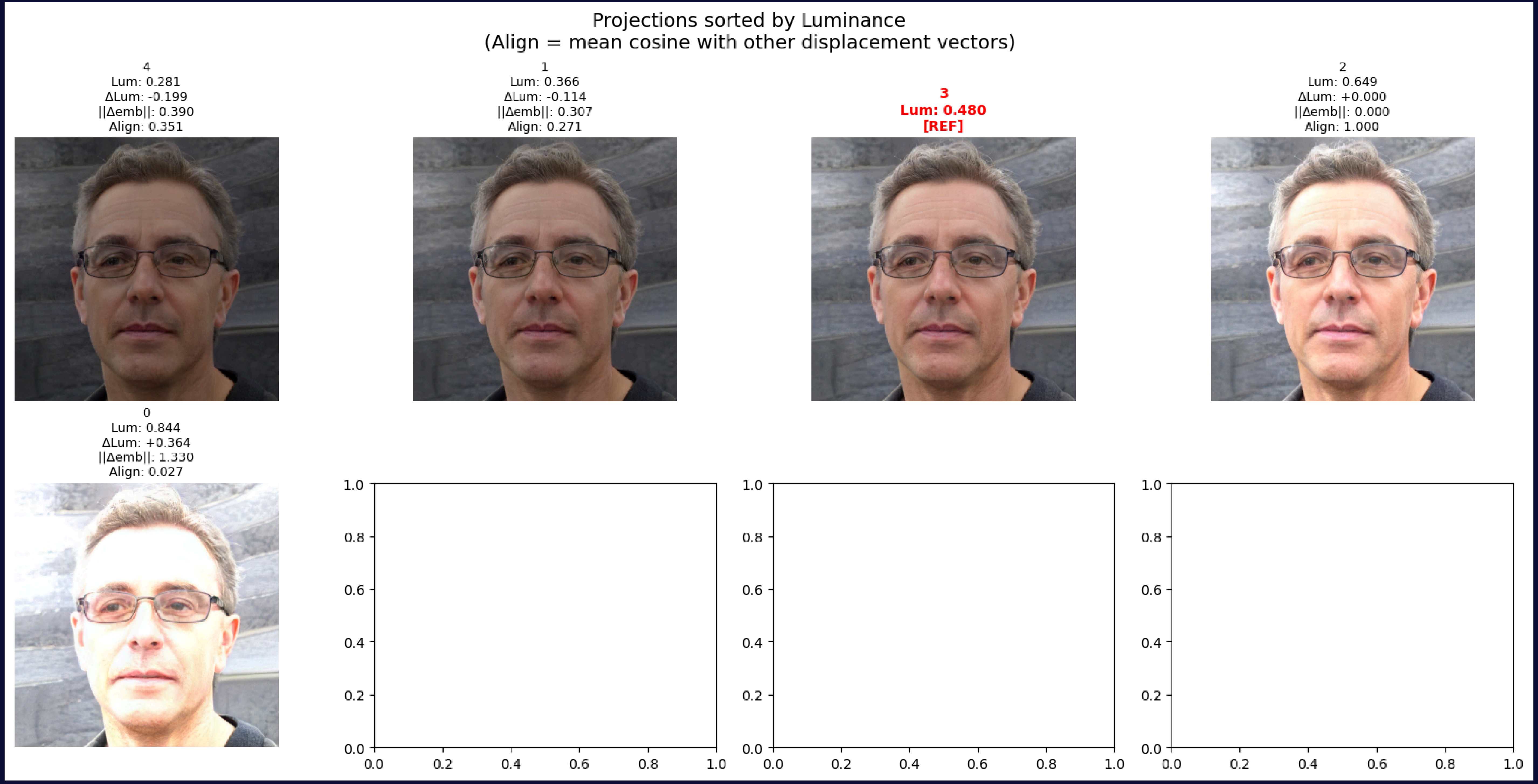
Use the extract embeddings from original projections.

```
H1 (mean directional illumination consistency): 0.21646247804164886
```



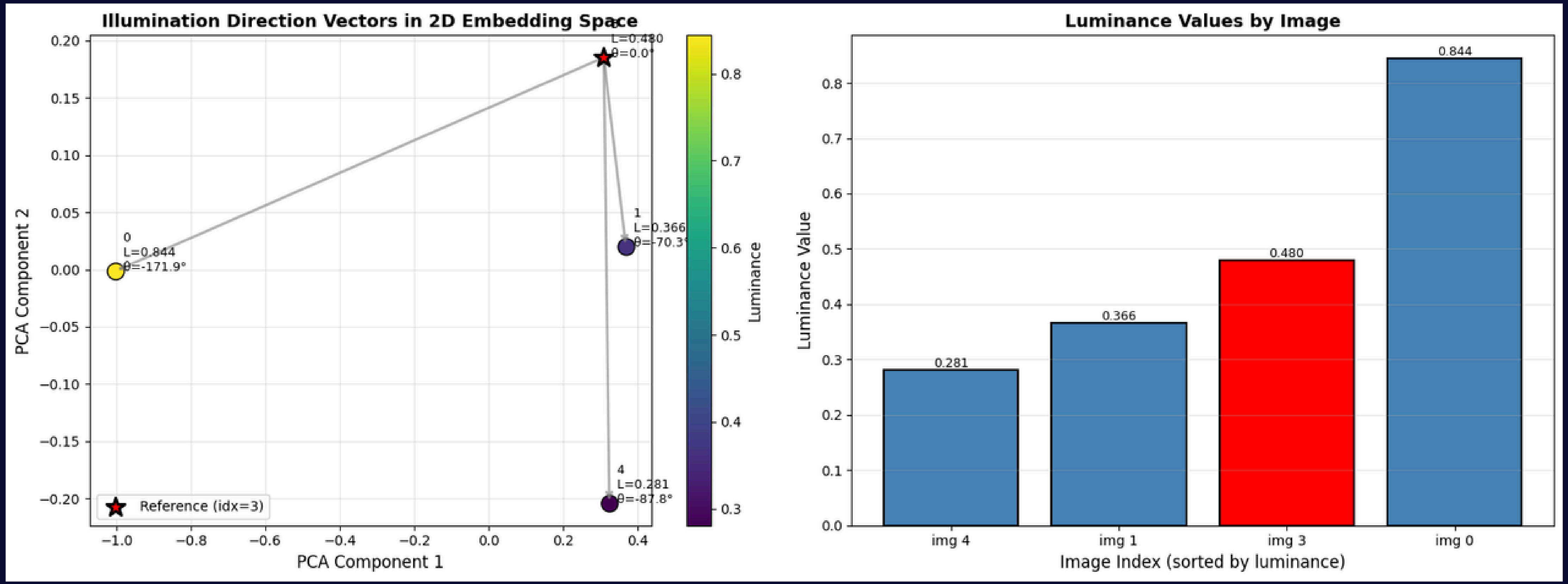
Results

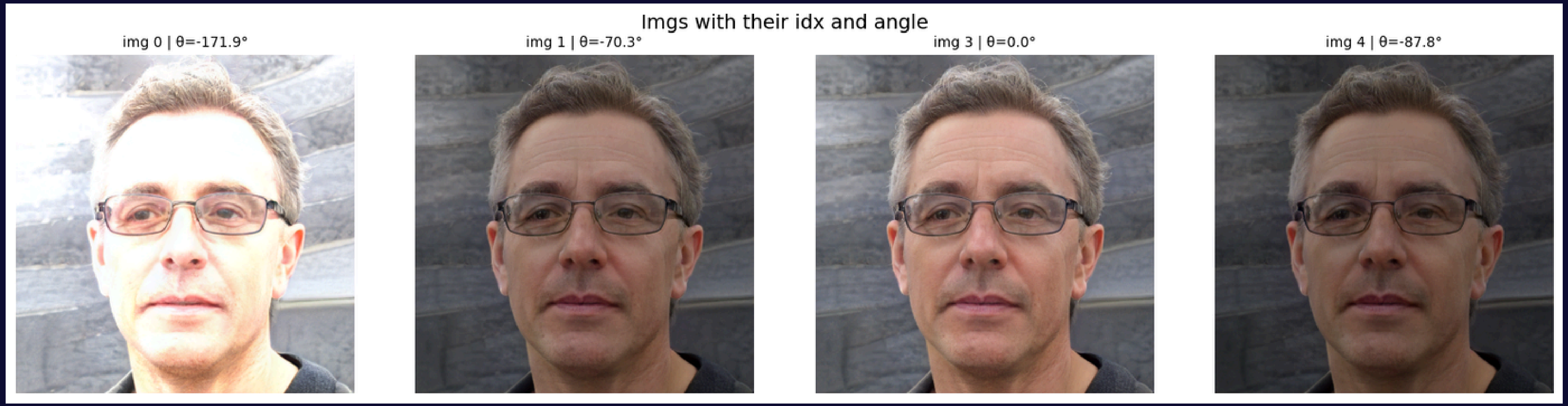
- Lum = diff of luminance
- Emb = how diff is the embedding between actual img and reference img
- Align = average cosine similarity between that img embedding change and the embedding changes of the other imgs, how much it points in the same direction as the rest. (close to 1, the best)



Results

- It only detected 4/5 faces of the 5 imgs
- Plot the illumination direction vectors from the reference img






```
PCA explained variance: [0.92119306 0.05232814]
Total variance explained: 0.9735212065279484
```

Analysis

- It caption the luminance of img how it increase between each img
- The darkest imgs (img 1,4)are more in the left side of the plot
- The lighter img (img 0) is on the left side, but have a greater angle than the darkest img (img 4)
- It could work that maybe the same luminance in one image is the same direction vector with the same angle.
- Maybe the ligther ones are in the negative side of PC1 and the darkest ones in the postive side PC2
- Maybe the darkest imgs with less luminance, it could be the same diffrence of luminance put in the lighter ones. But the darkest have less angle between them than the lighter ones
- Maybe it is on the extremes of low or high luminance its going to be in the negative side of PC2
- It has to be tried out with other imgs and a detector face more efficient maybe or better quality imgs (to analyze the pattern)

Tuesday

Meeting Alyssa

- Database CVRL faces
- Face Detector: RetinaFace
- Embedding: ArcFace
- Clusters by Identity
- Analyze geometry of the clusters
  - radius
  - dispersion of points
  - why does it have these characteristics? (eyes, old, hair color, sunglasses...)
  - dimensionality individual and in general all of he clusters
  - compare dimensionality between clusters
  - is it the same manifold
  - intrinsic dimensionality

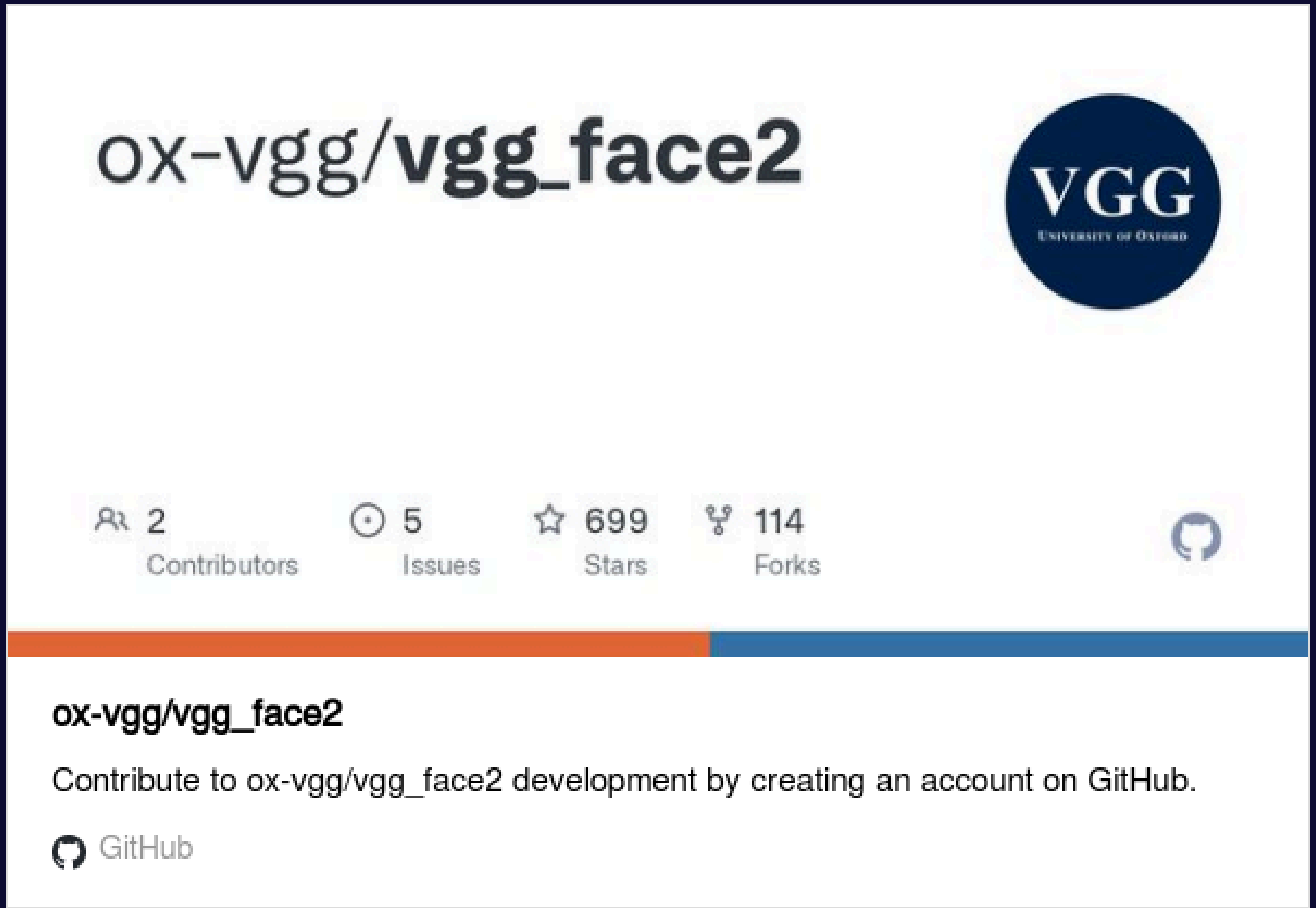
Meeting Alyssa

Optional

- StyleGAN2-ADA, generated database faces. Obtain the projection and compared to the projection of the real imgs. And then use ArcFace and compare the clusters if are the same or how different they are.
  - Compare multiple architectures
- Capacity, high representation to do classification (system design unsolvable)
- Method computational to manifold compares to other networks arhcitectures

Papers

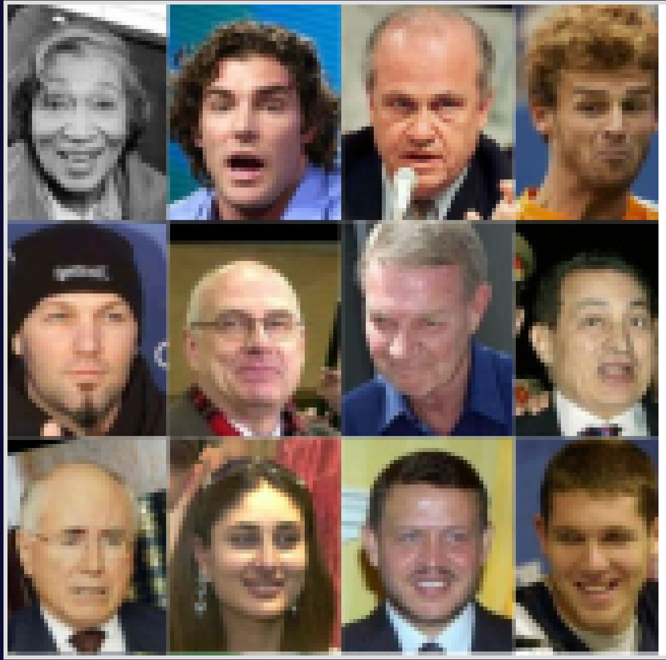
VGG2Face



Papers

LFW face recognition

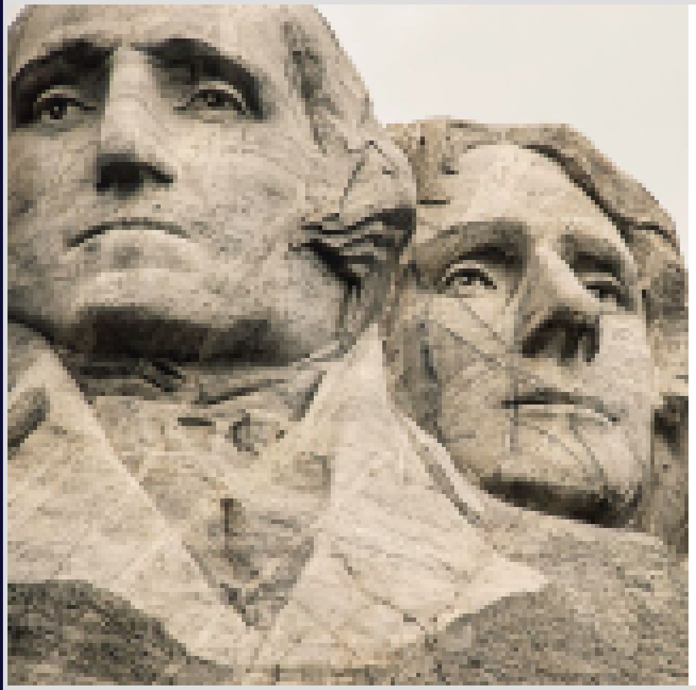
https://scikit-learn.org/0.19/datasets/labeled_faces.html



LFW - People (Face Recognition)

The Labeled Faces in the Wild face recognition dataset.

kaggle.com



Labelled Faces in the Wild (LFW) Dataset

Over 13,000 images of faces collected from the web

kaggle.com

Step by Step

1. Load images from scikit-learn, LFW / Load imgs and labels by identity
2. Initialize face detection + embeddings
3. Extract embeddings
4. Cluster by Identity
5. Intrinsic dimensionality
6. Visualization clusters
7. Cosine similarity between clusters (persons)
8. Analyze cluster stats
9. Scatter Plot: Intrinsic Dimension vs Cluster Dispersion
10. Scatter Plot: Radius vs Dispersion
11. Intrinsic Dimension
12. Scatter Plot: Radius and Number of Images

All Images from LFW

NO filter of number of images per identity

Step by Step

0. Setup

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import fetch_lfw_people
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
```

Step by Step

1. **Load imgs from LFW**

```
Images shape: (4324, 62, 47), Identities: 158
```

- (number of samples, h, w)
- Load imgs and labels by identity

2. **Initialize face detection + embeddings**

- Face Detection → RetinaFAce
- Extract embeddings → ArcFace

3. **Extract Embeddings**

```
Extracted embeddings shape: (4324, 512)
```

- Save embeddings and labels in a .csv

Step by Step

4. Cluster by Identity

- Cluster by identity
- Get cluster stats: centroid, radius, dispersion, number of imgs of 1 cluster

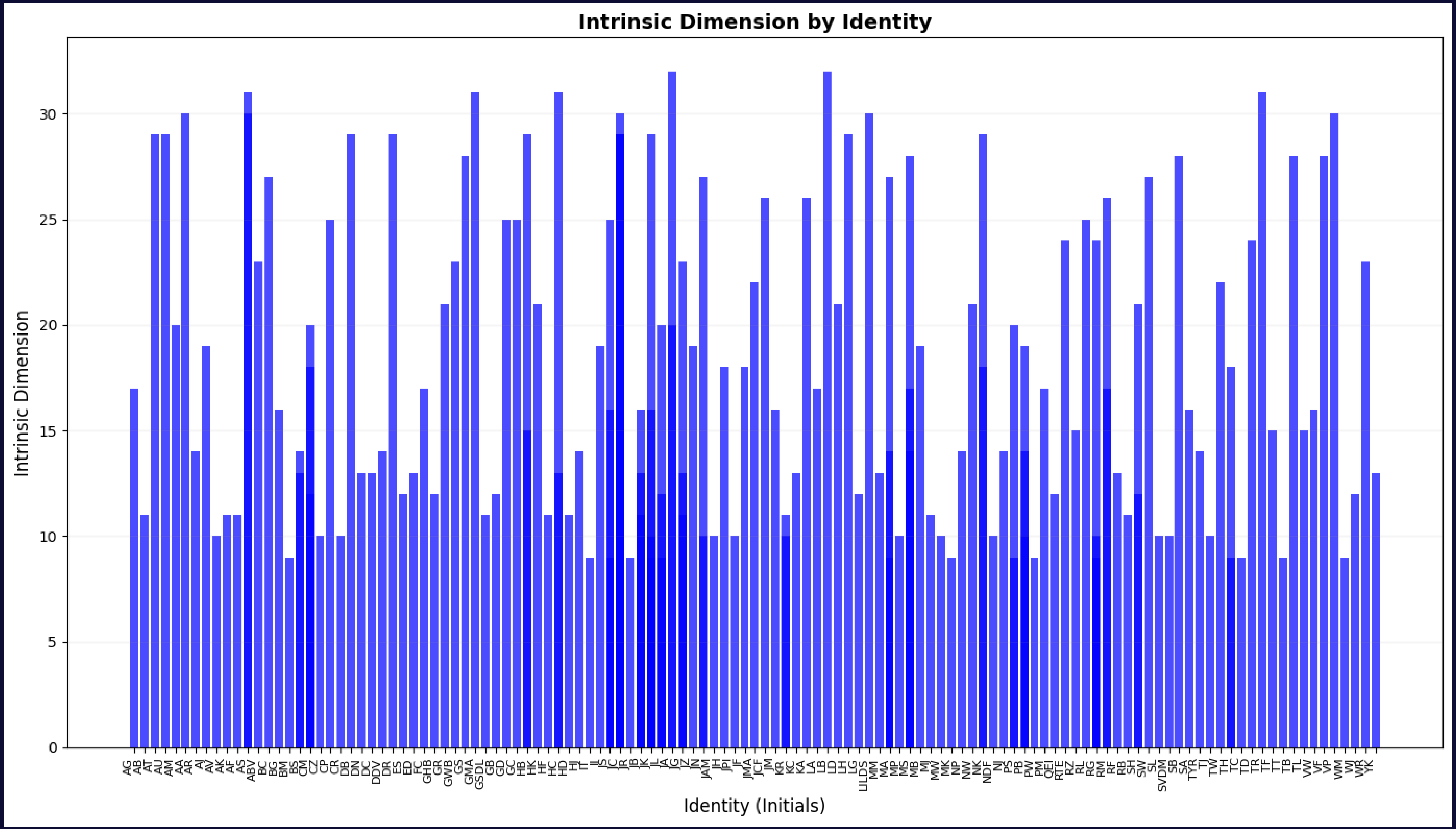
5. Intrinsic Dimensionality

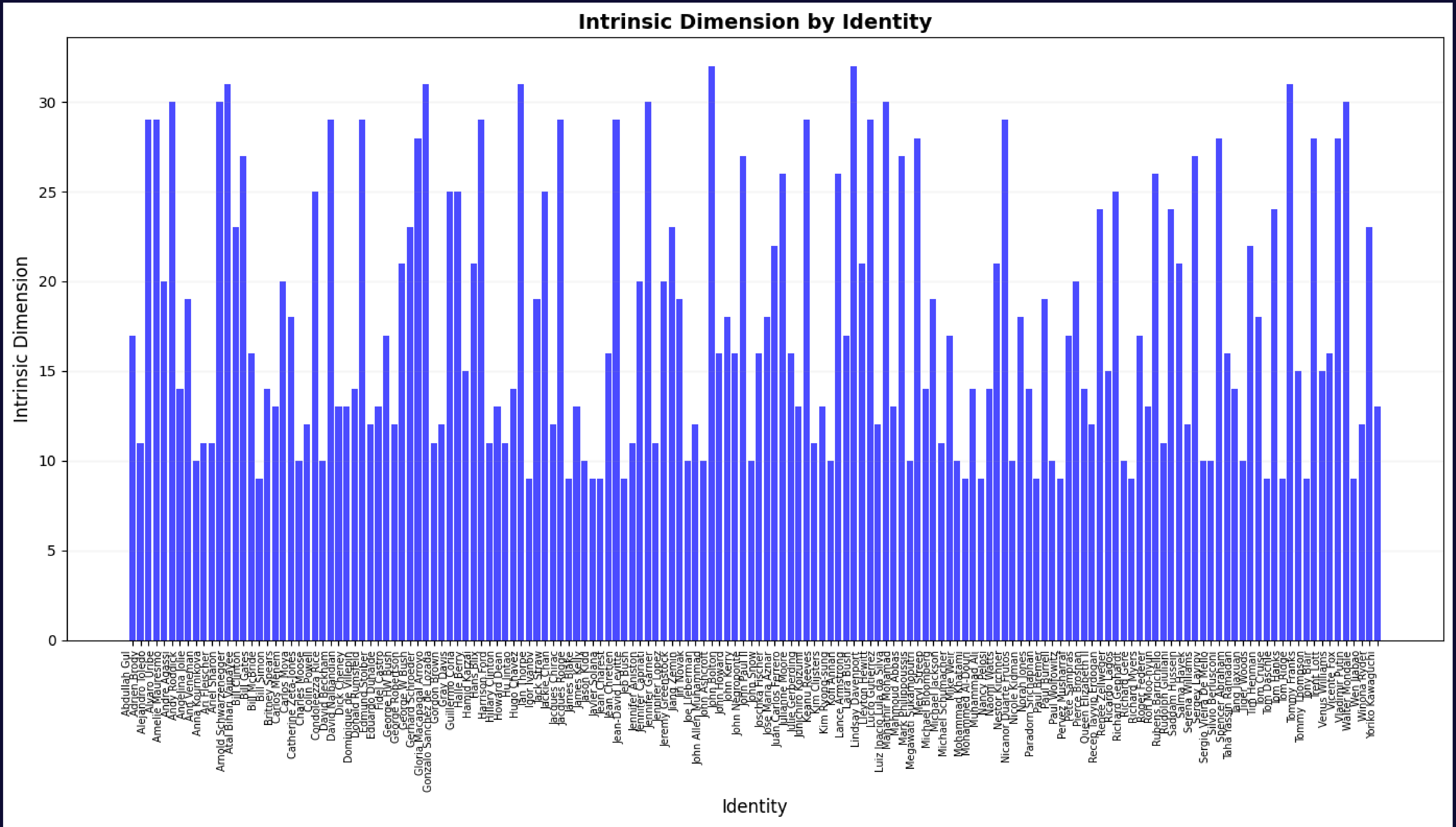
- Intrinsic dimension by identity
  - PCA.explained_variance_ratio_ > 0.01

```
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: Abdullah Gul, Intrinsic Dimension: 17
Identity: Adrien Brody, Intrinsic Dimension: 11
Identity: Alejandro Toledo, Intrinsic Dimension: 29
Identity: Alvaro Uribe, Intrinsic Dimension: 29
Identity: Amelie Mauresmo, Intrinsic Dimension: 20
Identity: Andre Agassi, Intrinsic Dimension: 30
Identity: Andy Roddick, Intrinsic Dimension: 14
Identity: Angelina Jolie, Intrinsic Dimension: 19
Identity: Ann Veneman, Intrinsic Dimension: 10
Identity: Anna Kournikova, Intrinsic Dimension: 11
Identity: Ari Fleischer, Intrinsic Dimension: 11
Identity: Ariel Sharon, Intrinsic Dimension: 30
Identity: Arnold Schwarzenegger, Intrinsic Dimension: 31
Identity: Atal Bihari Vajpayee, Intrinsic Dimension: 23
Identity: Bill Clinton, Intrinsic Dimension: 27
Identity: Bill Gates, Intrinsic Dimension: 16
Identity: Bill McBride, Intrinsic Dimension: 9
Identity: Bill Simon, Intrinsic Dimension: 14
Identity: Britney Spears, Intrinsic Dimension: 13
Identity: Carlos Menem, Intrinsic Dimension: 20
Identity: Carlos Moya, Intrinsic Dimension: 18
Identity: Catherine Zeta-Jones, Intrinsic Dimension: 10
Identity: Charles Moose, Intrinsic Dimension: 12
Identity: Colin Powell, Intrinsic Dimension: 25
Identity: Condoleezza Rice, Intrinsic Dimension: 10
...
```

- Plot by initials an then full name, to the intrinsic dimensionality

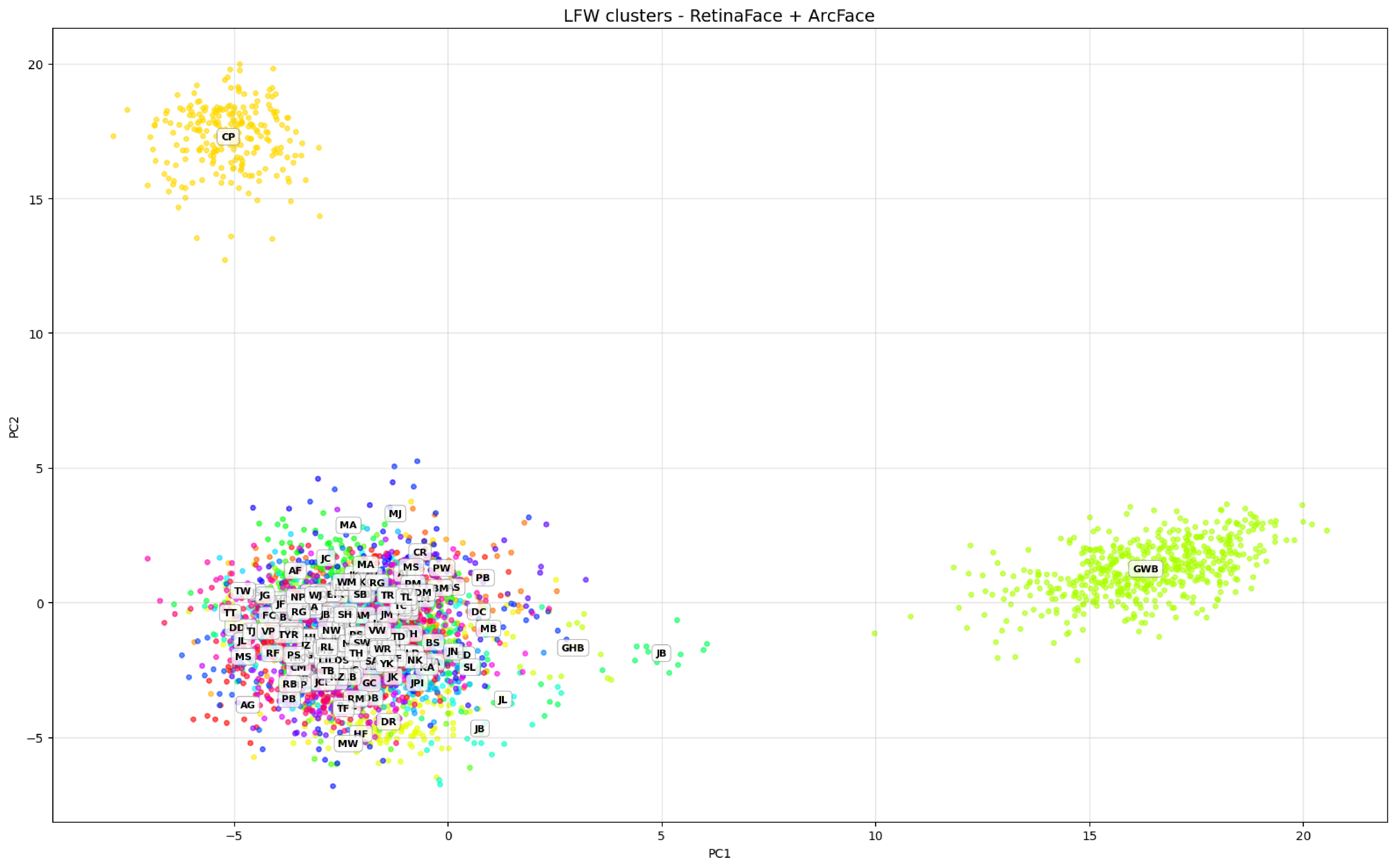




Intrinsic Dimension by Identity
Intrinsic Dimension
Identity
0
5
10
15
20
25
30

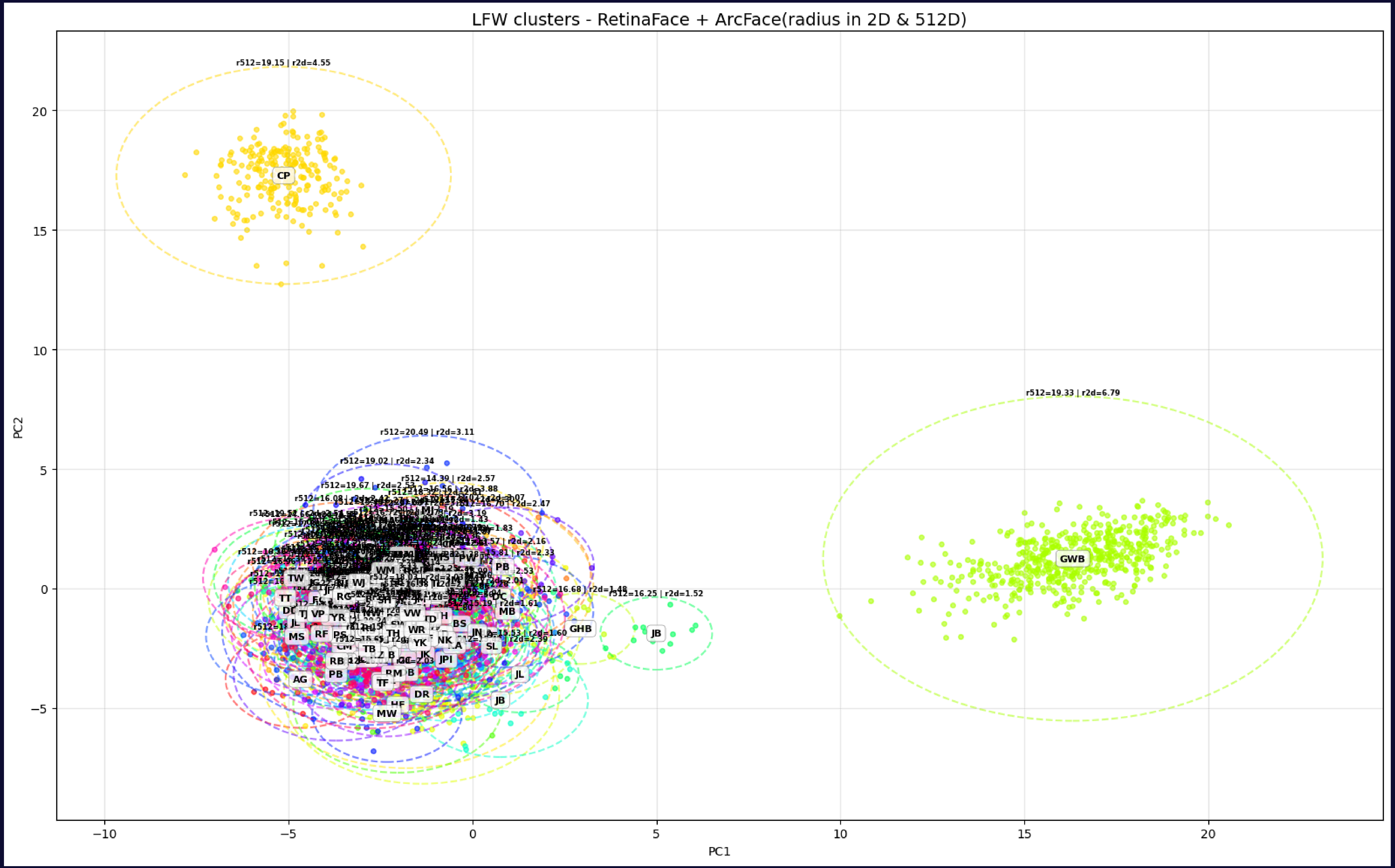
Step by Step

6. Visualization Clusters



Step by Step

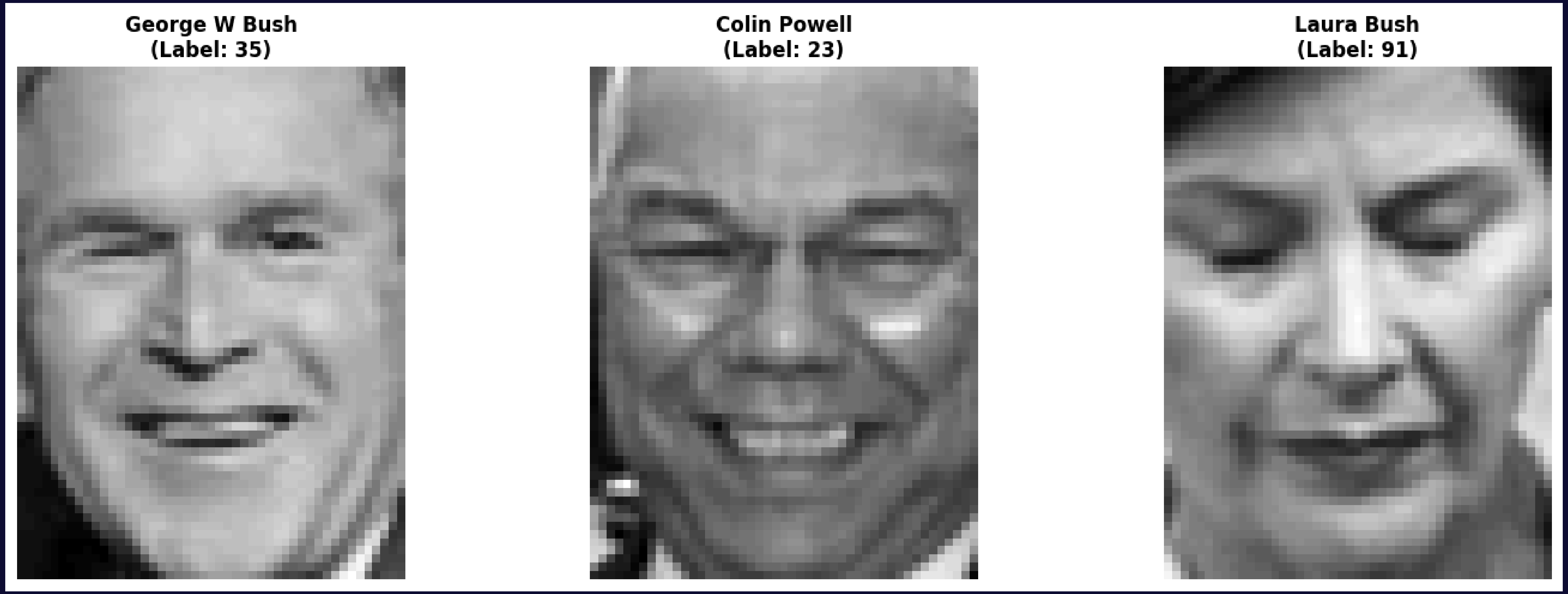
- Plot clusters and their radius in 512D and 2D



Step by Step

Analyze the 2 main clusters, with 1 cluster that it is overlap

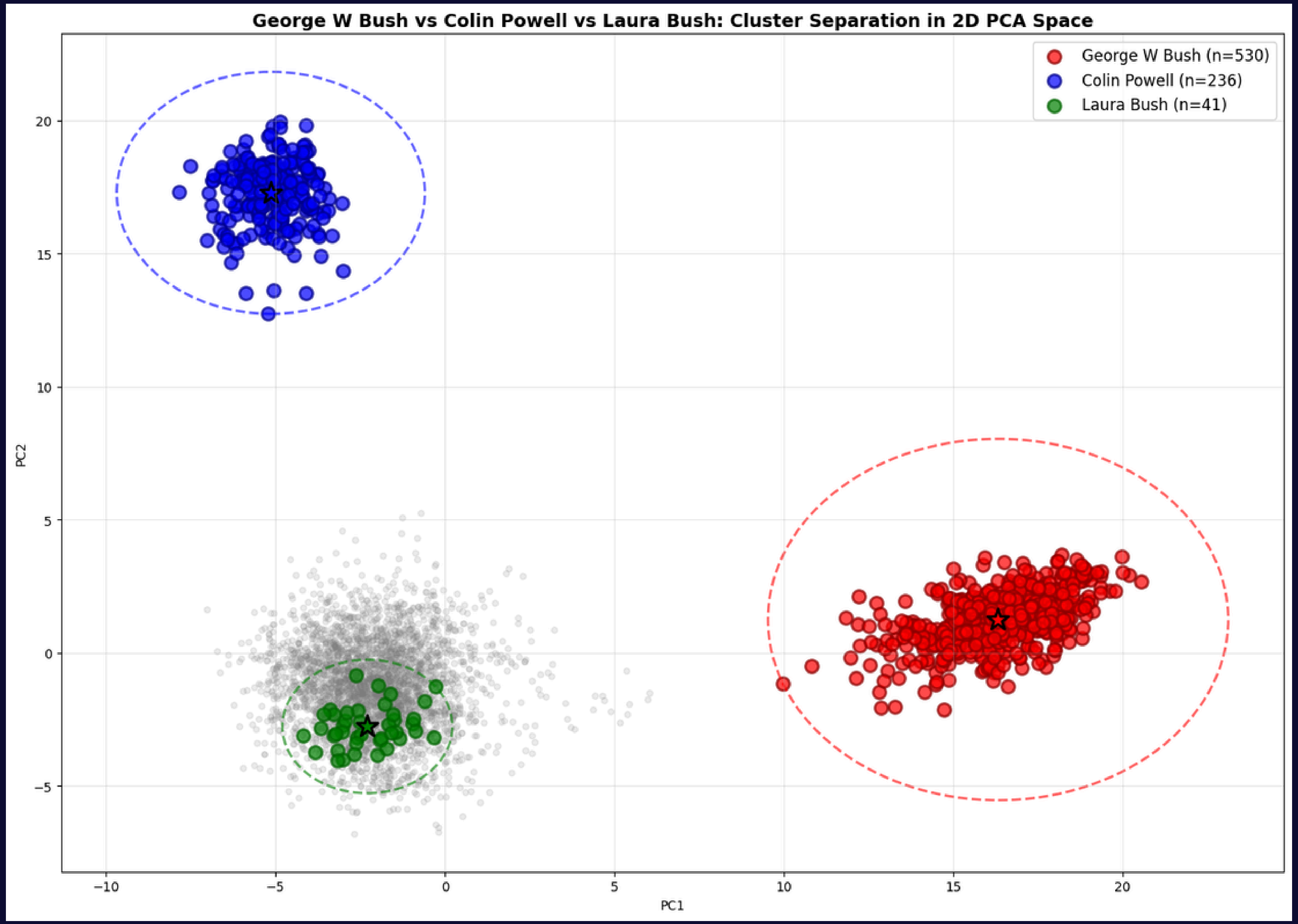
- See the faces of those identities and the label index



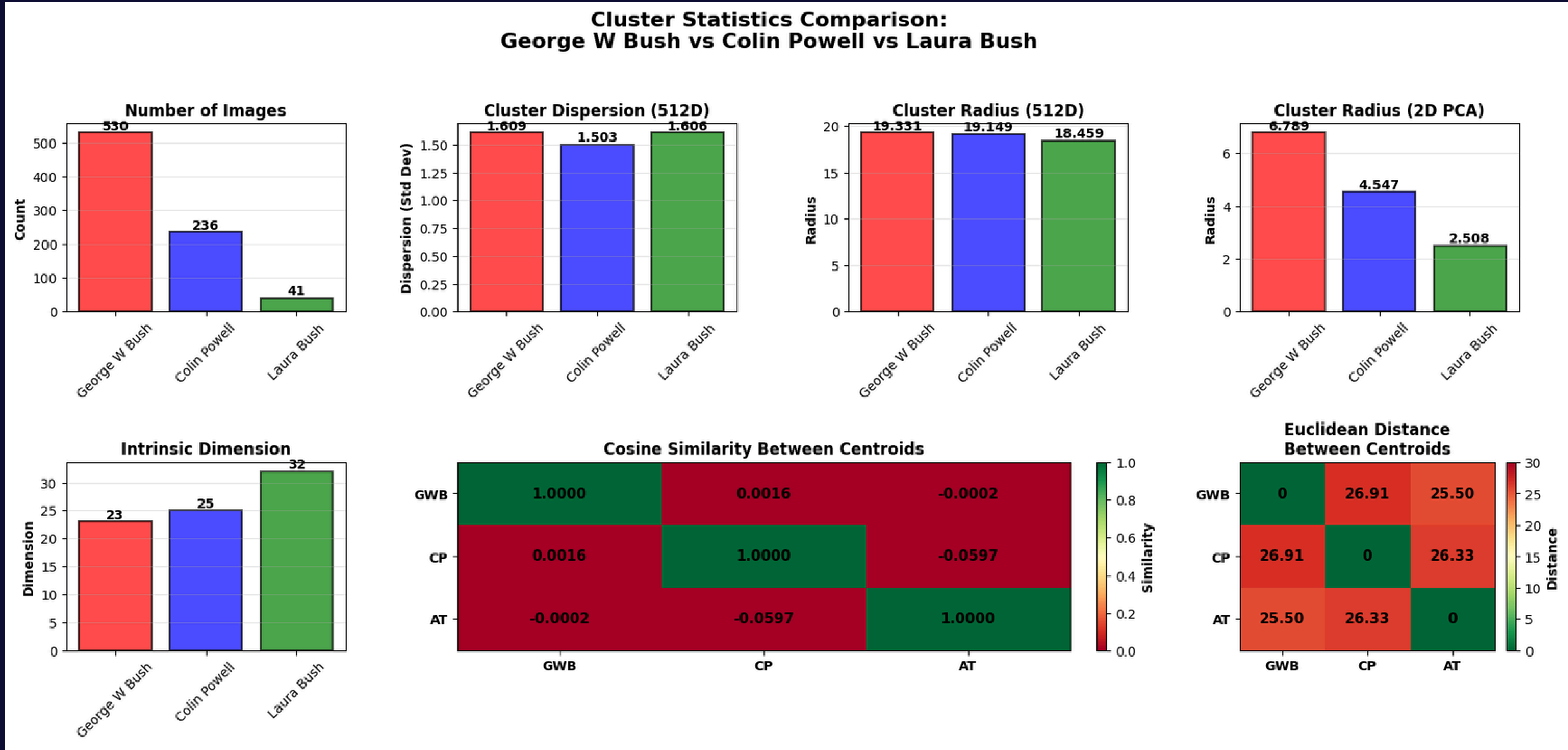
Step by Step

Analyze the 2 main clusters, with 1 cluster that it is overlap

- See the clusters seleceted to analyze.
- Compare the stats between them



Step by Step



Metric	George W Bush	Colin Powell	Laura Bush
Number of Images	**530**	**236**	**41**
Radius (512D)	**19.331116**	**19.149479**	**18.458601**
Dispersion (512D)	**1.6086893**	**1.5028448**	**1.6061269**
Intrinsic Dimension	**23**	**25**	**32**
Radius (2D PCA)	**6.788703**	**4.546931**	**2.5075235**

Step by Step

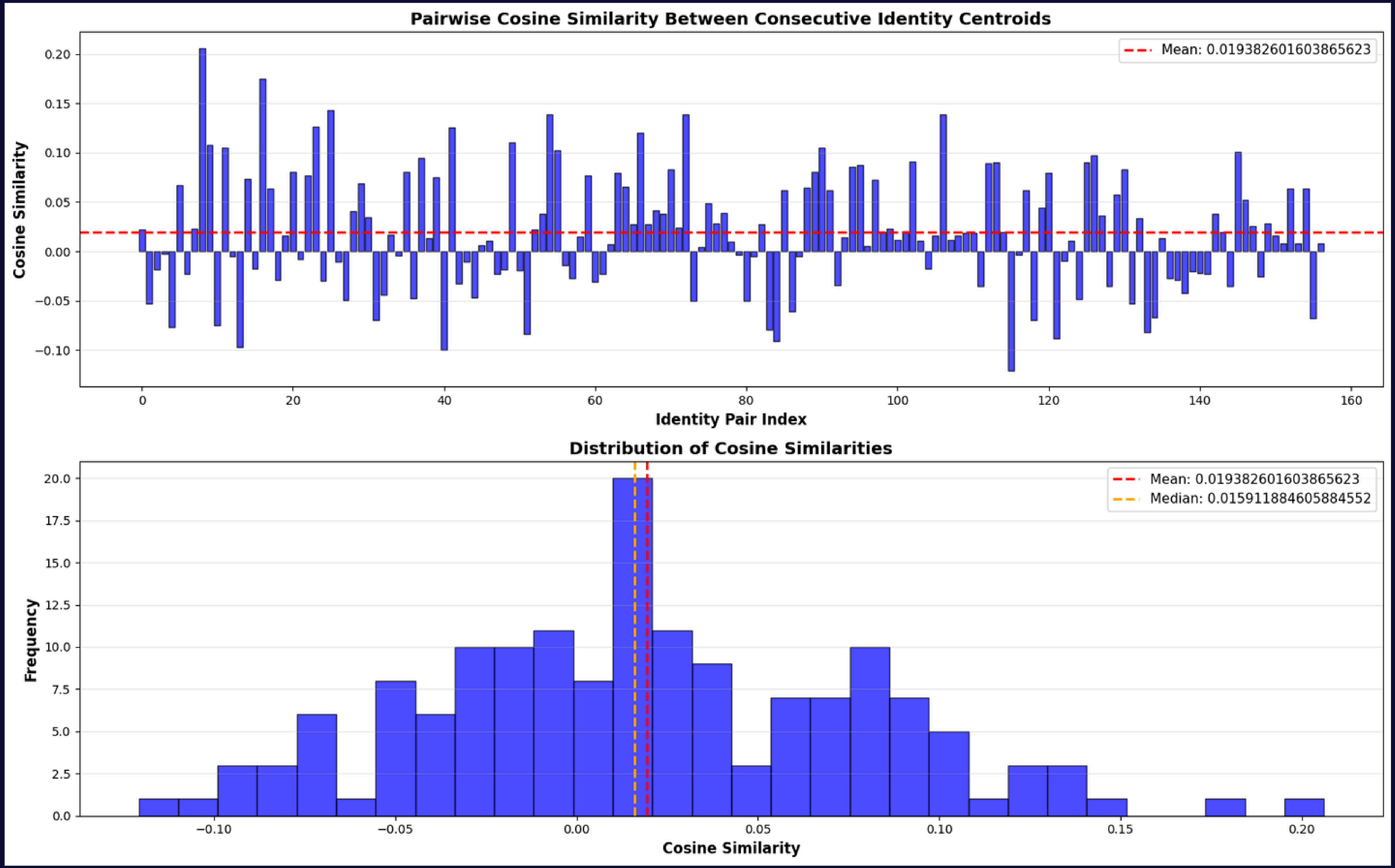
7. Cosine similarity between clusters (persons) using centroid

- Using cosine_similiraty from sklearn.metrics.pairwise

```
Cosine similarity Abdullah Gul vs Adrien Brody: 0.021794546395540237
Cosine similarity Adrien Brody vs Alejandro Toledo: -0.05306299403309822
Cosine similarity Alejandro Toledo vs Alvaro Uribe: -0.01882879249751568
Cosine similarity Alvaro Uribe vs Amelie Mauresmo: -0.0025038542225956917
Cosine similarity Amelie Mauresmo vs Andre Agassi: -0.07668893039226532
Cosine similarity Andre Agassi vs Andy Roddick: 0.0671813040971756
Cosine similarity Andy Roddick vs Angelina Jolie: -0.022662023082375526
Cosine similarity Angelina Jolie vs Ann Veneman: 0.02324599400162697
Cosine similarity Ann Veneman vs Anna Kournikova: 0.20612077414989471
Cosine similarity Anna Kournikova vs Ari Fleischer: 0.10760828852653503
Cosine similarity Ari Fleischer vs Ariel Sharon: -0.0748133510351181
Cosine similarity Ariel Sharon vs Arnold Schwarzenegger: 0.10506404936313629
Cosine similarity Arnold Schwarzenegger vs Atal Bihari Vajpayee: -0.00485227070748806
Cosine similarity Atal Bihari Vajpayee vs Bill Clinton: -0.09711261093616486
Cosine similarity Bill Clinton vs Bill Gates: 0.07314656674861908
Cosine similarity Bill Gates vs Bill McBride: -0.01738612726330757
Cosine similarity Bill McBride vs Bill Simon: 0.17490625381469727
Cosine similarity Bill Simon vs Britney Spears: 0.06332524120807648
Cosine similarity Britney Spears vs Carlos Menem: -0.028913166373968124
Cosine similarity Carlos Menem vs Carlos Moya: 0.016242824494838715
Cosine similarity Carlos Moya vs Catherine Zeta-Jones: 0.08078894019126892
Cosine similarity Catherine Zeta-Jones vs Charles Moose: -0.007595952600240707
Cosine similarity Charles Moose vs Colin Powell: 0.07687127590179443
Cosine similarity Colin Powell vs Condoleezza Rice: 0.12648215889930725
Cosine similarity Condoleezza Rice vs David Beckham: -0.03039529174566269
...
```

Step by Step

- How cosine similarities are distributed and their frequency




```
==================================================
COSINE SIMILARITY STATISTICS (Consecutive Pairs):
==================================================
Mean similarity: 0.019382601603865623
Median similarity: 0.015911884605884552
Std deviation: 0.06011653319001198
Min similarity: -0.12082041054964066
Max similarity: 0.20612077414989471
```

Step by Step

8. Analyze cluster stats

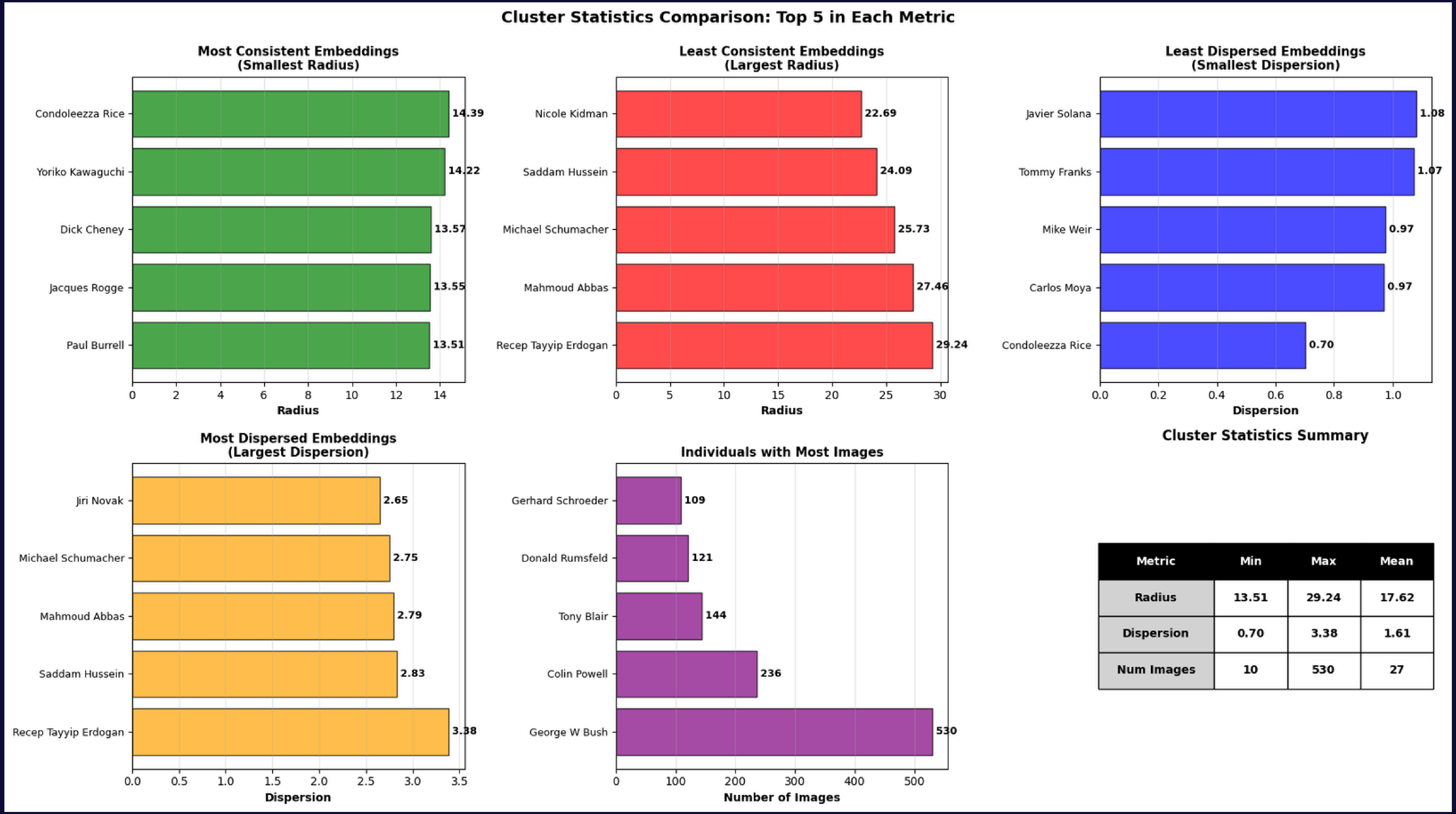
- Cluster data to dataframe for better visualization
- Summary for the stats with count, mean, std, min,max, 25%,50%,75%
- Merged data frame with intrinsic dimension

Summary Statistics for Merged DataFrame:

	intrinsic_dimension	radius	dispersion	num_images
count	158.000000	158.000000	158.000000	158.000000
mean	17.632911	17.617338	1.611169	27.367089
std	7.224652	2.188553	0.393341	47.598822
min	9.000000	13.514051	0.703220	10.000000
25%	11.000000	16.367286	1.342523	12.000000
50%	16.000000	17.333834	1.537392	17.000000
75%	24.000000	18.541212	1.803914	26.000000
max	32.000000	29.241322	3.383645	530.000000

Step by Step

- Top 5 smallest/largest radius, smallest/largest dispersion and most images
- Min,max and average for: radius, dispersion, num imgs

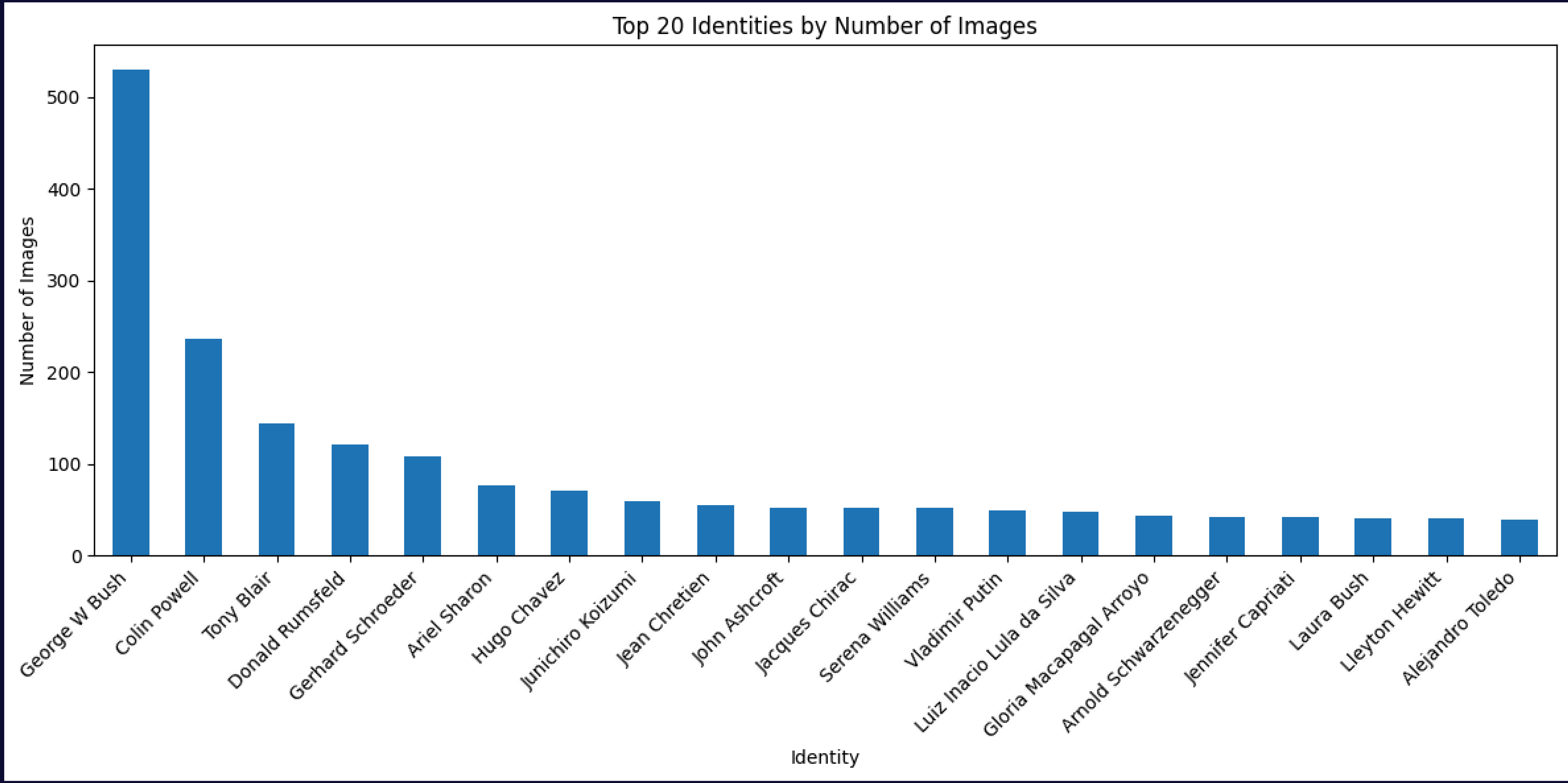


Step by Step

- **Smallest Radius = small average distance of ther embeddings from their centroids**
  - So face embeddings are tightly clustered
  - So they have higher consistency across different imgs of the same person
- **Largest Radius = largest average distance from their centroids.**
  - So face embeddings are more spread out
  - So they have less consistency or greater variation in their imgs
- **Smallest Dispersion = small deviation of distances from their centroids**
  - So the variation in embedding consistency are very low
- **Largest Dispersion = largest deviation of distances**
  - So they have more variability in the consistency of their embeddings.
  - High dispersion = wider range of conditions in the imgs (pose, light, expression...)

Step by Step

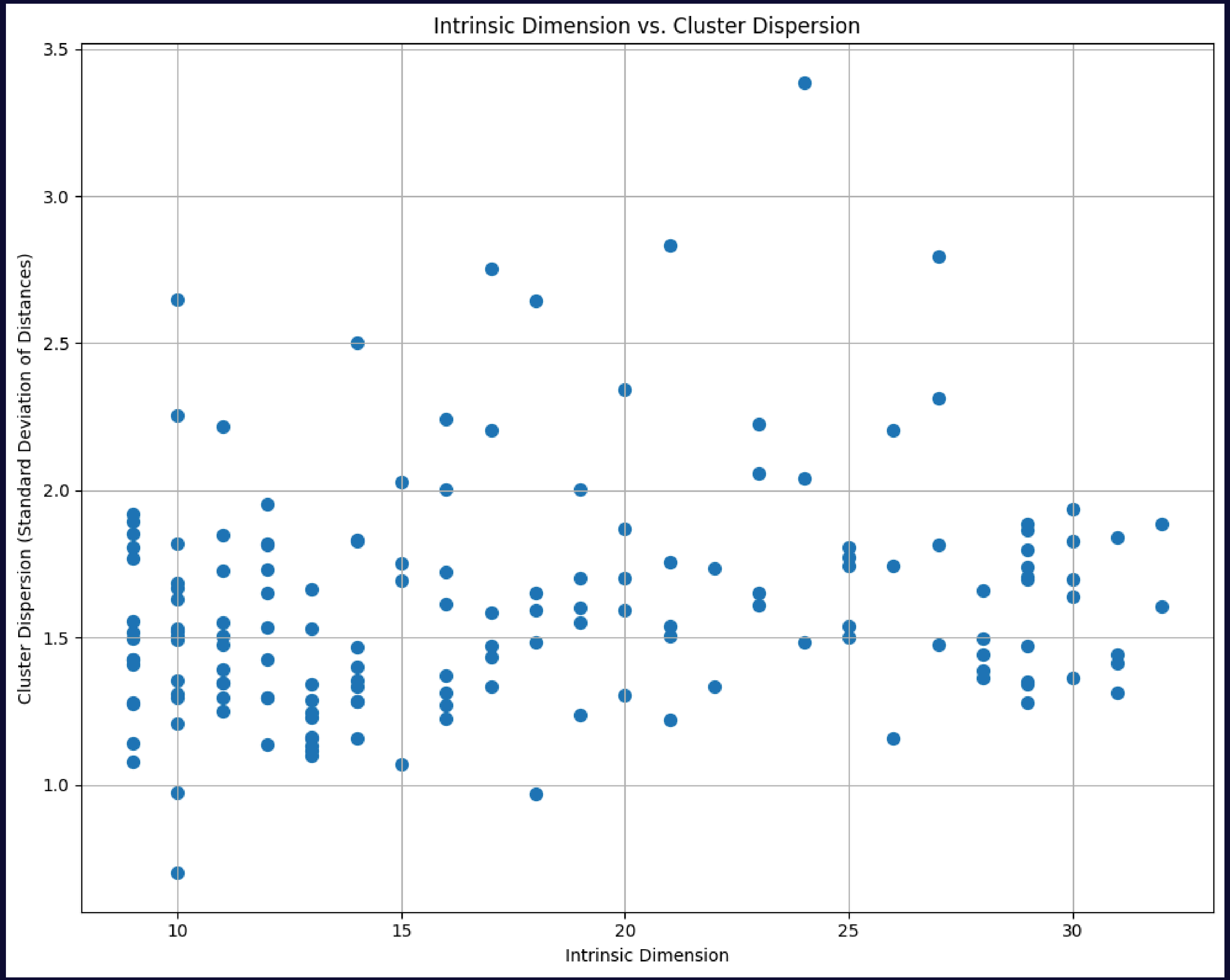
- Number of imgs per identity
- Only top 20



Step by Step

9. Scatter Plot: Intrinsic Dimension vs Cluster Dispersion

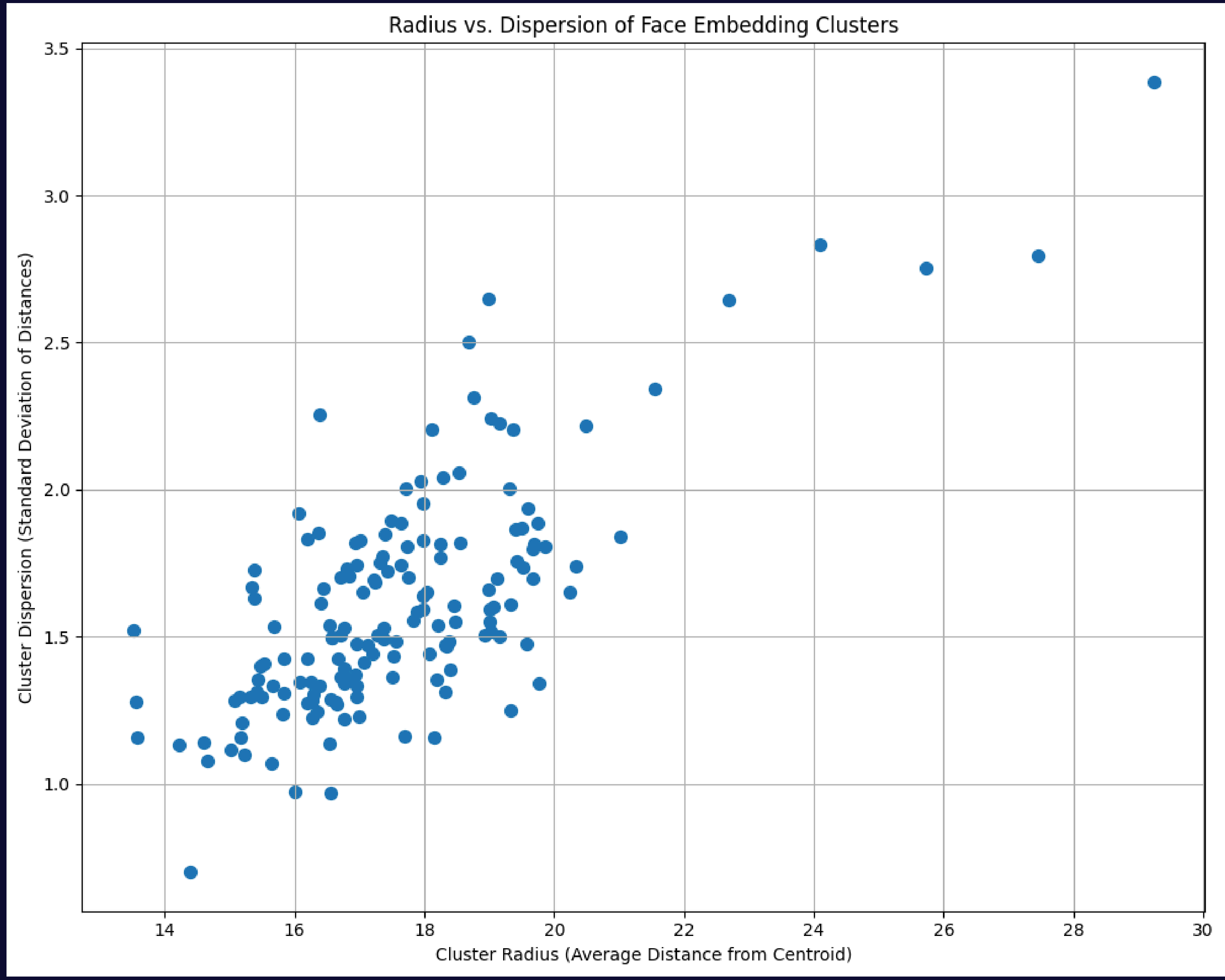
- A liite of: Higher dispersion values for identities with higher intrinsic dimensions



Step by Step

10. **Scatter Plot: Radius vs Dispersion**

- Higher radius, higher cluster dispersion



Step by Step

11. Intrinsic Dimension

- Identities with the 10 highest and lowest intrinsic dim
- HIgh Intrinsic Dimension:
  - imgs clusters have a greater variability or complexity
  - More principal components are needed to explain the variance within their respective clusters.
  - May be to a wider range of poses, expressions, lighting conditions, or image quality variations.
- Less Intrinsic Dimension:
  - img clusters are less complex or more consistent.
  - Fewer principal components are sufficient to capture the variance within their embeddings.
  - Maybe the images for these individuals are more uniform.
- Low Dimensional Manifold: low intrinsic dim 9-32, compared to 512D embedding space.

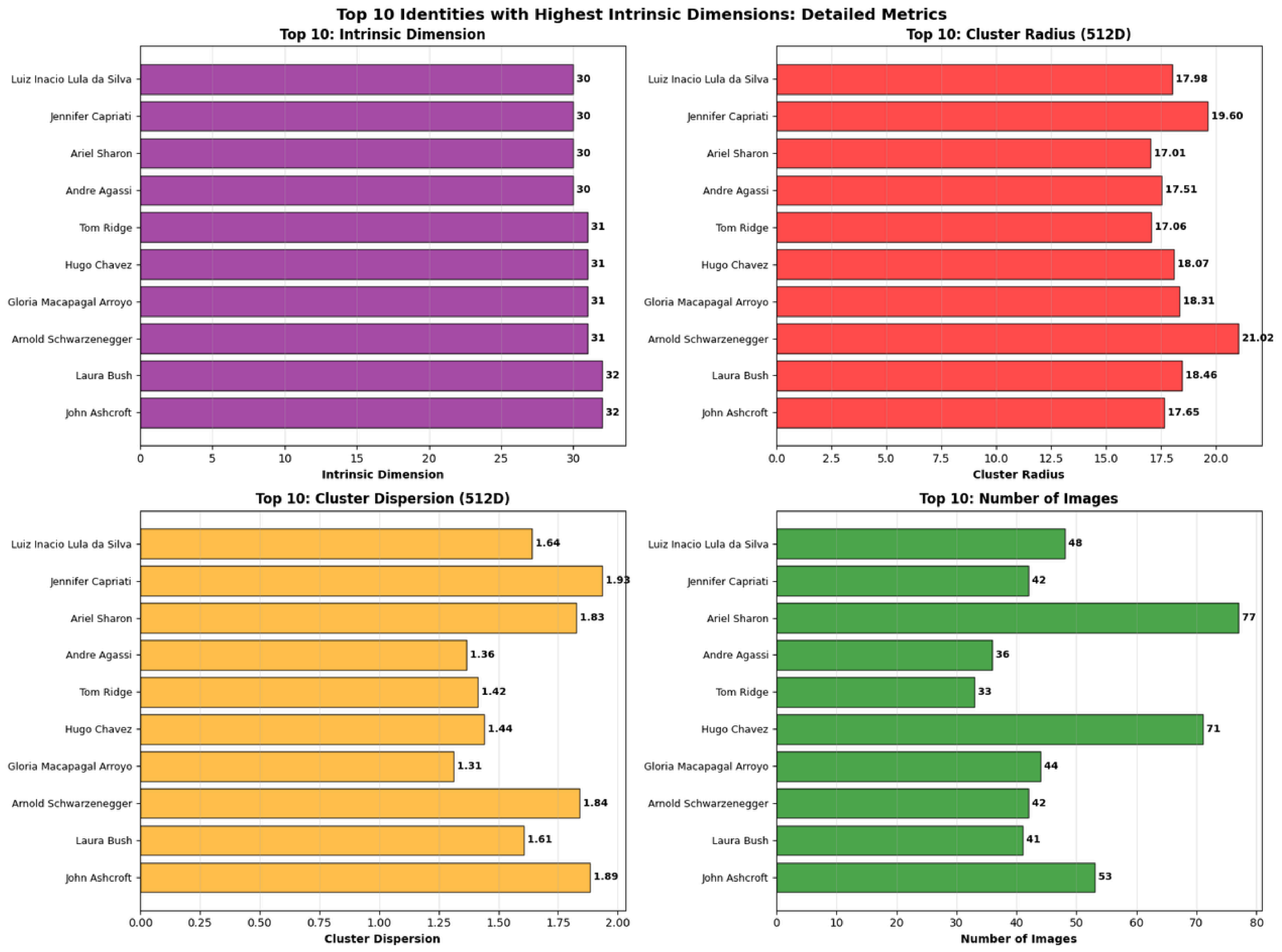
```
Descriptive Statistics for Intrinsic Dimensionality:
count    158.000000
mean      17.632911
std        7.224652
min        9.000000
25%       11.000000
50%       16.000000
75%       24.000000
max       32.000000
Name: intrinsic_dimension, dtype: float64
```

```
Identities with the 10 highest intrinsic dimensions:
                           intrinsic_dimension
Laura Bush                                  32
John Ashcroft                               32
Tom Ridge                                   31
Gloria Macapagal Arroyo                     31
Hugo Chavez                                 31
Arnold Schwarzenegger                       31
Luiz Inacio Lula da Silva                   30
Andre Agassi                                30
Jennifer Capriati                           30
Vladimir Putin                              30

Identities with the 10 lowest intrinsic dimensions:
                    intrinsic_dimension
Muhammad Ali                          9
Jason Kidd                            9
Javier Solana                         9
Ian Thorpe                            9
Jean-David Levitte                    9
Mohammad Khatami                      9
Paradorn Srichaphan                   9
Paul Wolfowitz                        9
Richard Gere                          9
Bill McBride                          9
```

Step by Step

- Top 10 identites with high intrinsic dimension metrics to see relationship between other metrics
- Compare to min, max and average values of the metrics



Cluster Statistics Summary

Metric	Max	Min	Mean
Radius (512D)	29.24	13.51	17.62
Dispersion	3.38	0.70	1.61
Num Images	530	10	27

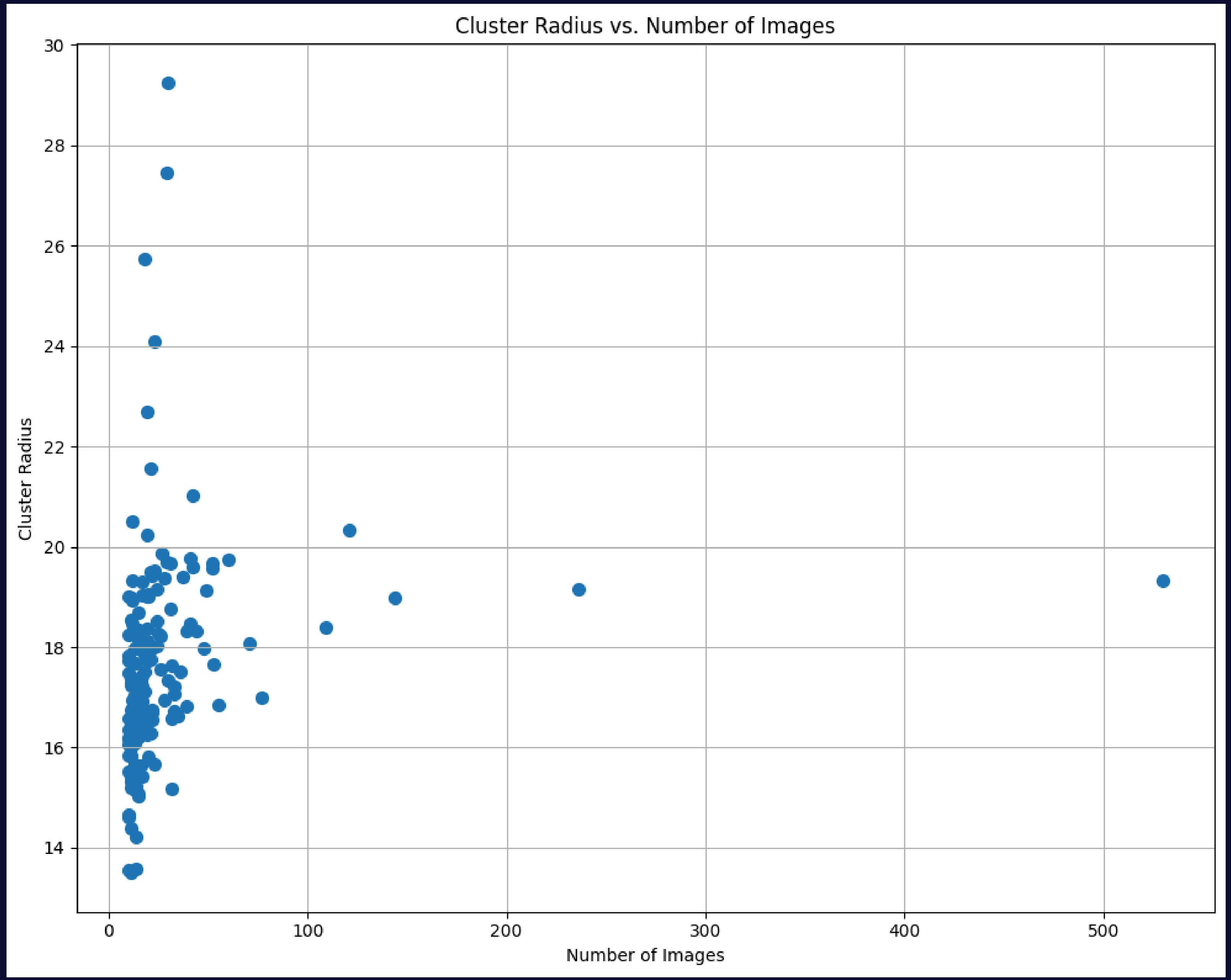
Top 10 Identities with Highest Intrinsic Dimensions

Identity	Intrinsic Dim	Radius	Dispersion	Num Images
John Ashcroft	32	17.65	1.89	53
Laura Bush	32	18.46	1.61	41
Arnold Schwarzenegger	31	21.02	1.84	42
Gloria Macapagal Arroyo	31	18.31	1.31	44
Hugo Chavez	31	18.07	1.44	71
Tom Ridge	31	17.06	1.42	33
Andre Agassi	30	17.51	1.36	36
Ariel Sharon	30	17.01	1.83	77
Jennifer Capriati	30	19.60	1.93	42
Luiz Inacio Lula da Silva	30	17.98	1.64	48

Step by Step

12. Scatter Plot: Radius and Number of Images

- No strong linear correlation between them
- Even with few images some identities have very consistent embeddings, while others can be quite inconsistent



Wednesday

COMPARING

Filter 10-25 imgs per identity
Filter 10-15 imgs per identity
Filter 5-10 imgs per identity

Number of identities by the filter

All imgs

```
Images shape: (4324, 62, 47), Identities: 158
```

10-25 imgs

```
Filtered number of identities: 117
Images shape: (4324, 62, 47)
```

10-15 imgs

```
Filtered number of identities: 73
Images shape: (4324, 62, 47)
```

5-10 imgs

```
Filtered number of identities: 15
Images shape: (4324, 62, 47)
```

Intrinsic Dimensionality

All imgs

```
Identity: Abdullah Gul, Intrinsic Dimension: 17
Identity: Adrien Brody, Intrinsic Dimension: 11
Identity: Alejandro Toledo, Intrinsic Dimension: 29
Identity: Alvaro Uribe, Intrinsic Dimension: 29
Identity: Amelie Mauresmo, Intrinsic Dimension: 20
Identity: Andre Agassi, Intrinsic Dimension: 30
Identity: Andy Roddick, Intrinsic Dimension: 14
Identity: Angelina Jolie, Intrinsic Dimension: 19
Identity: Ann Veneman, Intrinsic Dimension: 10
Identity: Anna Kournikova, Intrinsic Dimension: 11
Identity: Ari Fleischer, Intrinsic Dimension: 11
Identity: Ariel Sharon, Intrinsic Dimension: 30
Identity: Arnold Schwarzenegger, Intrinsic Dimension: 31
Identity: Atal Bihari Vajpayee, Intrinsic Dimension: 23
Identity: Bill Clinton, Intrinsic Dimension: 27
Identity: Bill Gates, Intrinsic Dimension: 16
Identity: Bill McBride, Intrinsic Dimension: 9
Identity: Bill Simon, Intrinsic Dimension: 14
Identity: Britney Spears, Intrinsic Dimension: 13
Identity: Carlos Menem, Intrinsic Dimension: 20
Identity: Carlos Moya, Intrinsic Dimension: 18
Identity: Catherine Zeta-Jones, Intrinsic Dimension: 10
Identity: Charles Moose, Intrinsic Dimension: 12
Identity: Colin Powell, Intrinsic Dimension: 25
Identity: Condoleezza Rice, Intrinsic Dimension: 10
...
```

10-15 imgs

```
Identity: Adrien Brody, Intrinsic Dimension: 11
Identity: Andy Roddick, Intrinsic Dimension: 14
Identity: Ann Veneman, Intrinsic Dimension: 10
Identity: Anna Kournikova, Intrinsic Dimension: 11
Identity: Ari Fleischer, Intrinsic Dimension: 11
Identity: Bill McBride, Intrinsic Dimension: 9
Identity: Bill Simon, Intrinsic Dimension: 14
Identity: Britney Spears, Intrinsic Dimension: 13
Identity: Catherine Zeta-Jones, Intrinsic Dimension: 10
Identity: Charles Moose, Intrinsic Dimension: 12
Identity: Condoleezza Rice, Intrinsic Dimension: 10
Identity: David Nalbandian, Intrinsic Dimension: 13
Identity: Dick Cheney, Intrinsic Dimension: 13
Identity: Dominique de Villepin, Intrinsic Dimension: 14
Identity: Edmund Stoiber, Intrinsic Dimension: 12
Identity: Eduardo Duhalde, Intrinsic Dimension: 13
Identity: George HW Bush, Intrinsic Dimension: 12
Identity: Gonzalo Sanchez de Lozada, Intrinsic Dimension: 11
Identity: Gordon Brown, Intrinsic Dimension: 12
Identity: Harrison Ford, Intrinsic Dimension: 11
Identity: Hillary Clinton, Intrinsic Dimension: 13
Identity: Howard Dean, Intrinsic Dimension: 11
Identity: Hu Jintao, Intrinsic Dimension: 14
Identity: Ian Thorpe, Intrinsic Dimension: 9
Identity: Jackie Chan, Intrinsic Dimension: 12
...
```

10-25 imgs

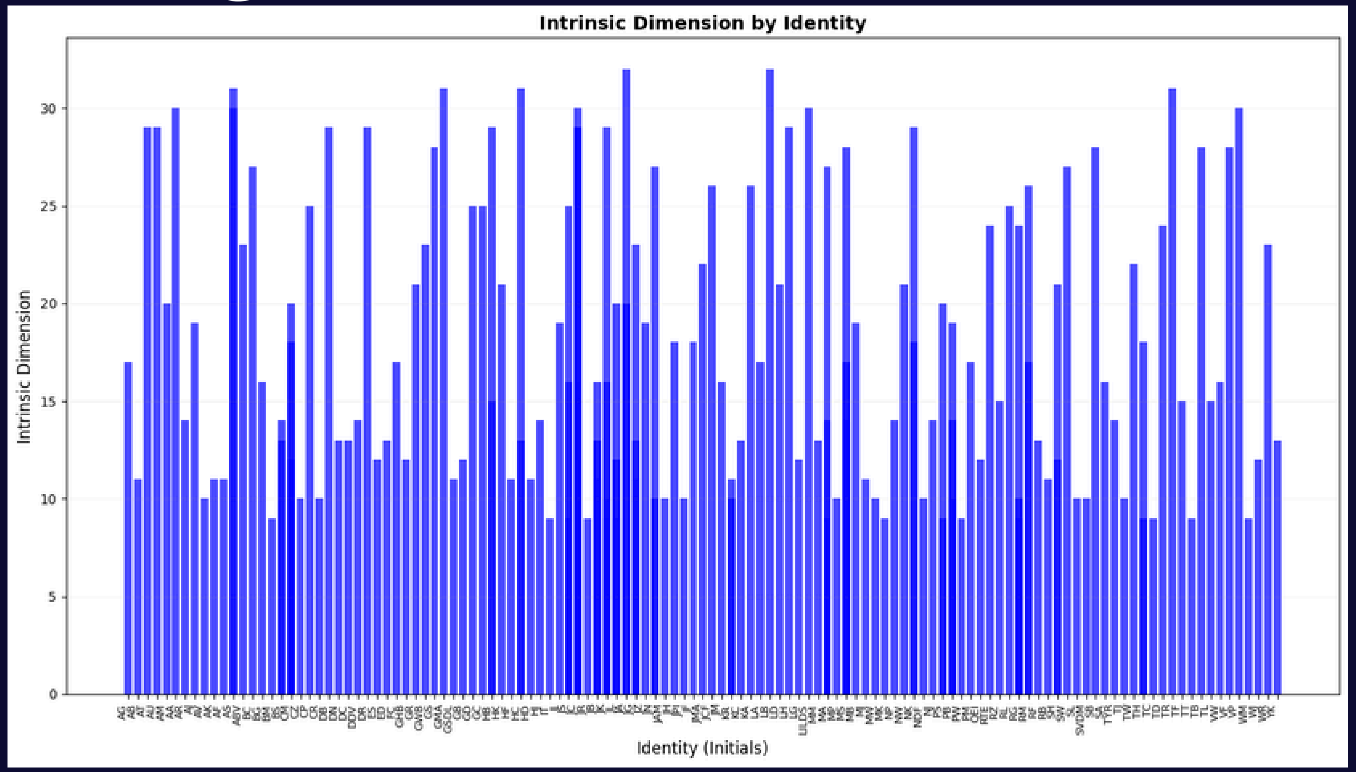
```
Identity: Abdullah Gul, Intrinsic Dimension: 17
Identity: Adrien Brody, Intrinsic Dimension: 11
Identity: Amelie Mauresmo, Intrinsic Dimension: 20
Identity: Andy Roddick, Intrinsic Dimension: 14
Identity: Angelina Jolie, Intrinsic Dimension: 19
Identity: Ann Veneman, Intrinsic Dimension: 10
Identity: Anna Kournikova, Intrinsic Dimension: 11
Identity: Ari Fleischer, Intrinsic Dimension: 11
Identity: Atal Bihari Vajpayee, Intrinsic Dimension: 23
Identity: Bill Gates, Intrinsic Dimension: 16
Identity: Bill McBride, Intrinsic Dimension: 9
Identity: Bill Simon, Intrinsic Dimension: 14
Identity: Britney Spears, Intrinsic Dimension: 13
Identity: Carlos Menem, Intrinsic Dimension: 20
Identity: Carlos Moya, Intrinsic Dimension: 18
Identity: Catherine Zeta-Jones, Intrinsic Dimension: 10
Identity: Charles Moose, Intrinsic Dimension: 12
Identity: Condoleezza Rice, Intrinsic Dimension: 10
Identity: David Nalbandian, Intrinsic Dimension: 13
Identity: Dick Cheney, Intrinsic Dimension: 13
Identity: Dominique de Villepin, Intrinsic Dimension: 14
Identity: Edmund Stoiber, Intrinsic Dimension: 12
Identity: Eduardo Duhalde, Intrinsic Dimension: 13
Identity: Fidel Castro, Intrinsic Dimension: 17
Identity: George HW Bush, Intrinsic Dimension: 12
...
```

5-10 imgs

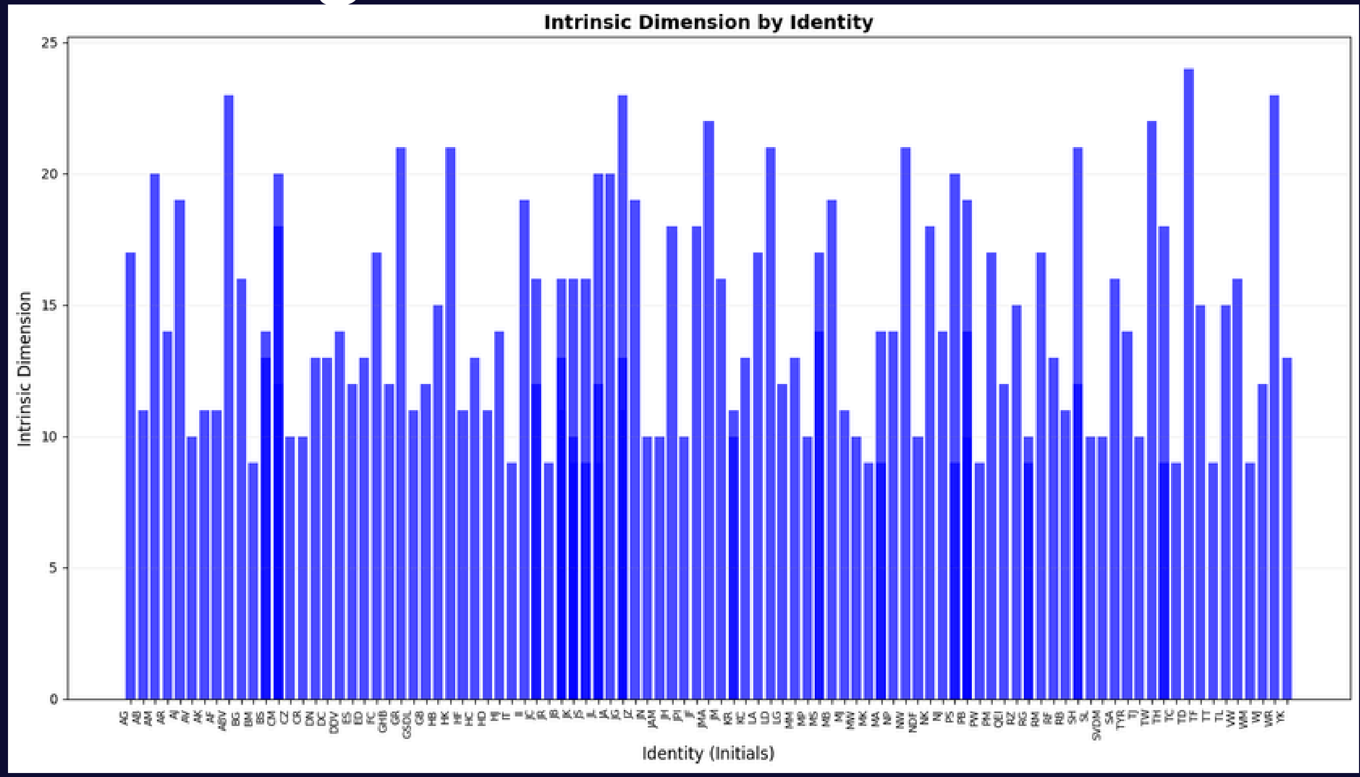
```
Identity: Bill McBride, Intrinsic Dimension: 9
Identity: Ian Thorpe, Intrinsic Dimension: 9
Identity: Jacques Rogge, Intrinsic Dimension: 9
Identity: Jason Kidd, Intrinsic Dimension: 9
Identity: Javier Solana, Intrinsic Dimension: 9
Identity: Jean-David Levitte, Intrinsic Dimension: 9
Identity: Mohammad Khatami, Intrinsic Dimension: 9
Identity: Muhammad Ali, Intrinsic Dimension: 9
Identity: Paradorn Srichaphan, Intrinsic Dimension: 9
Identity: Paul Wolfowitz, Intrinsic Dimension: 9
Identity: Richard Gere, Intrinsic Dimension: 9
Identity: Tom Cruise, Intrinsic Dimension: 9
Identity: Tom Hanks, Intrinsic Dimension: 9
Identity: Tommy Thompson, Intrinsic Dimension: 9
Identity: Walter Mondale, Intrinsic Dimension: 9
```

Intrinsic Dimensionality (initials)

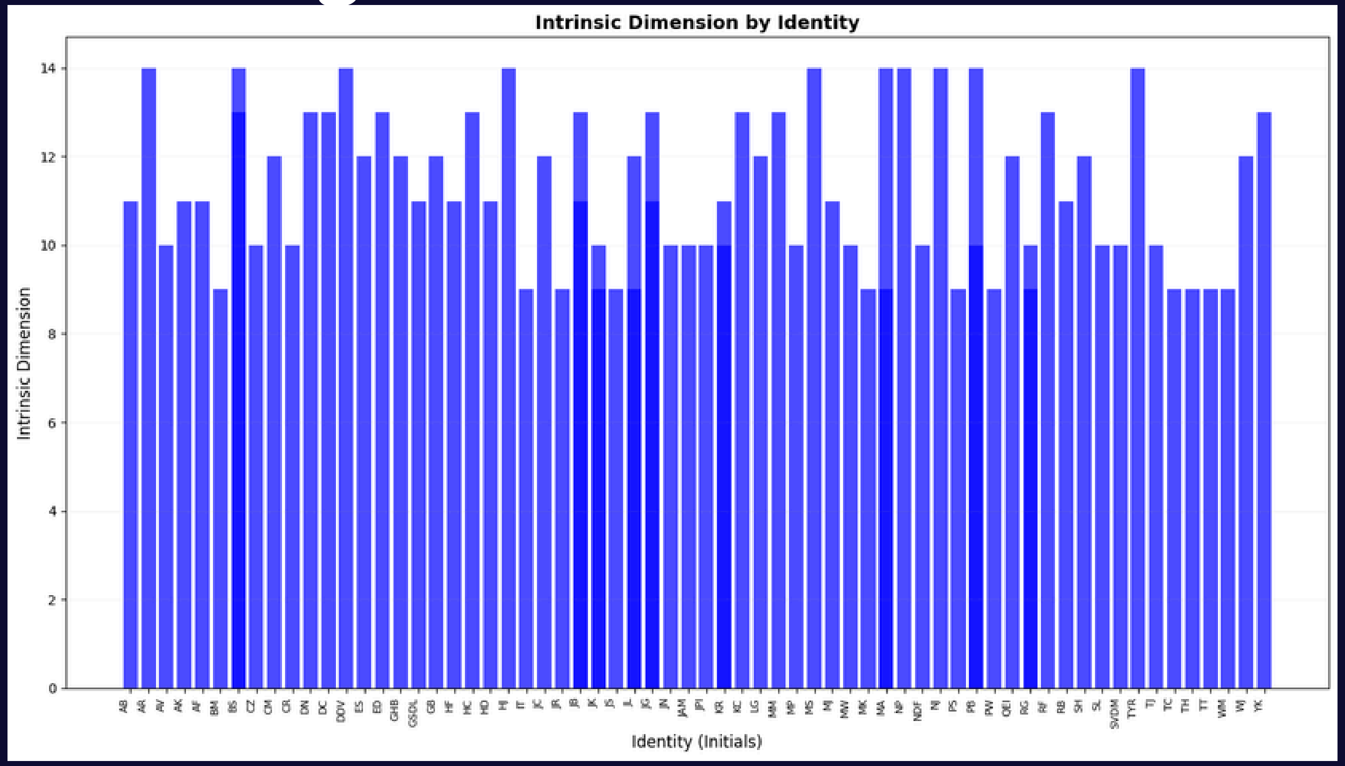
All imgs



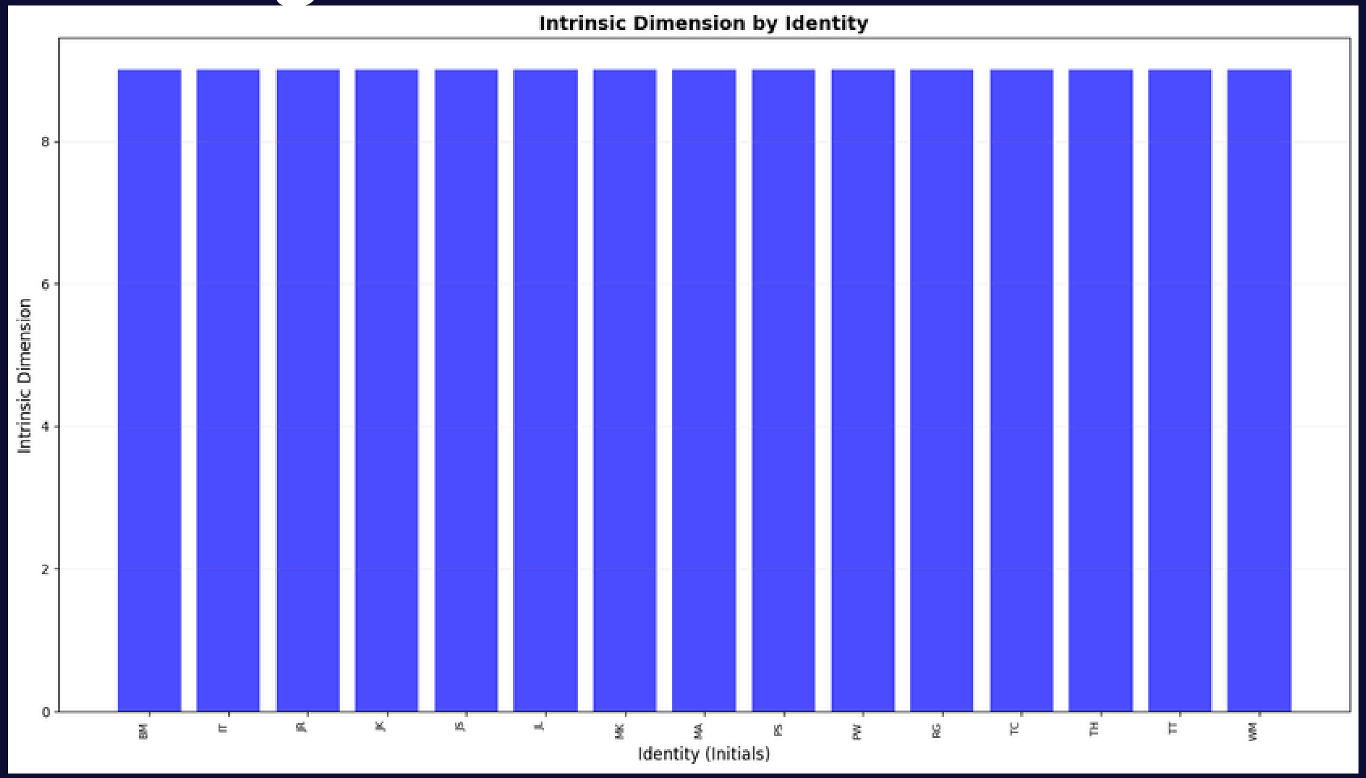
10-25 imgs



10-15 imgs

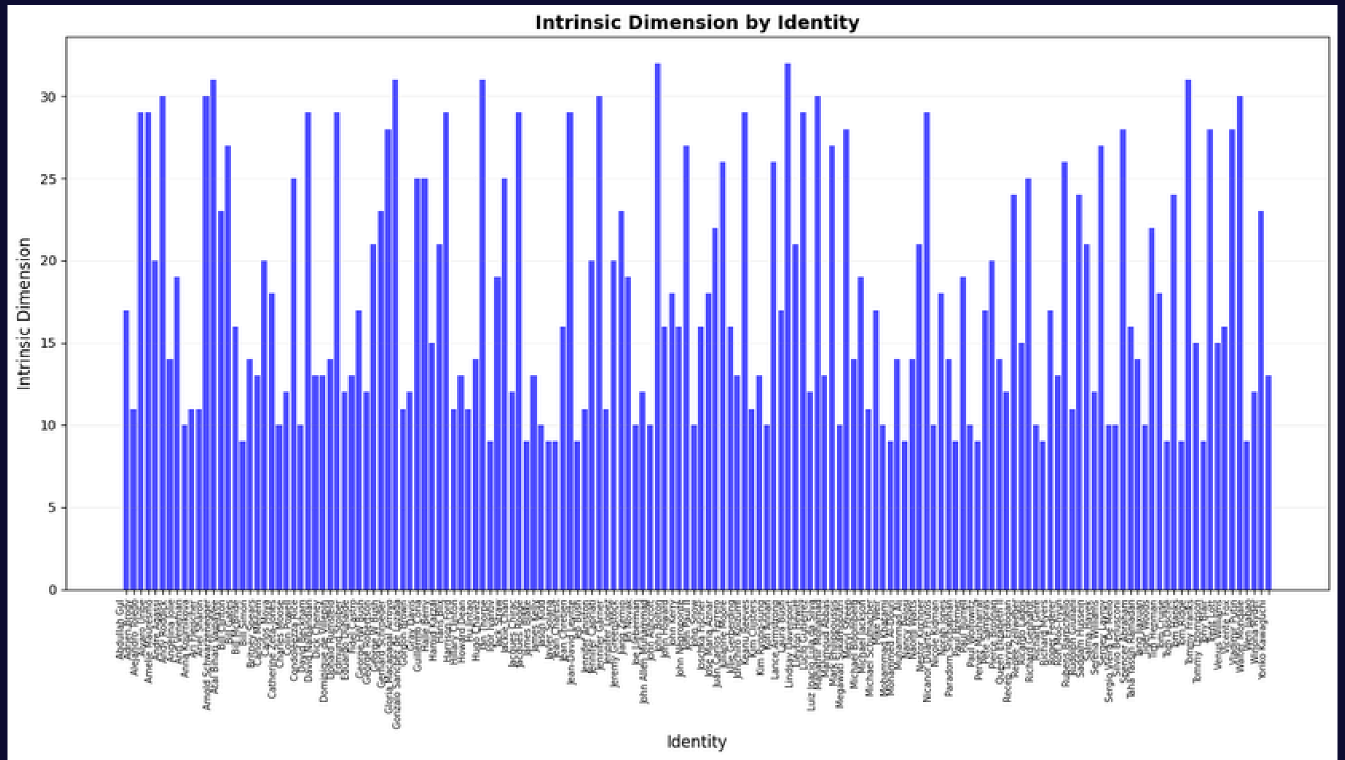


5-10 imgs

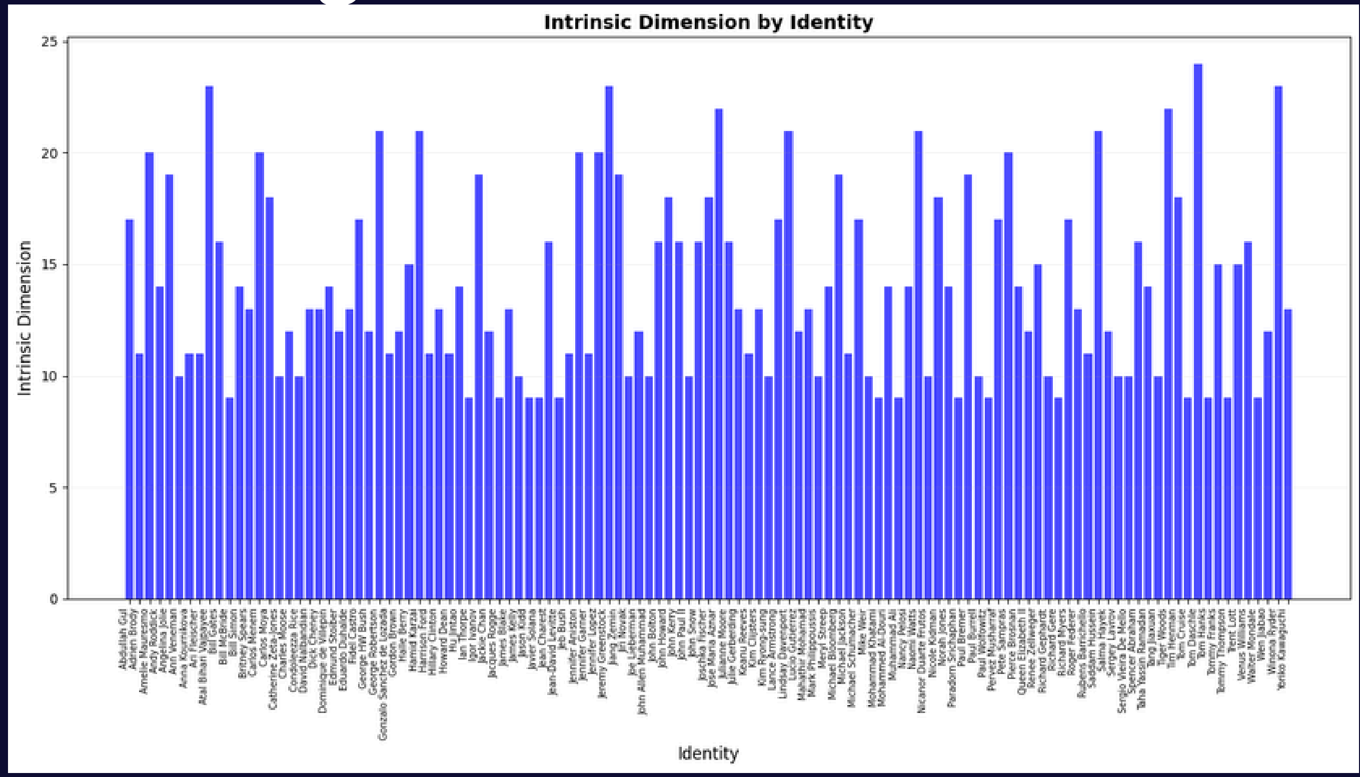


Intrinsic Dimensionality (full name)

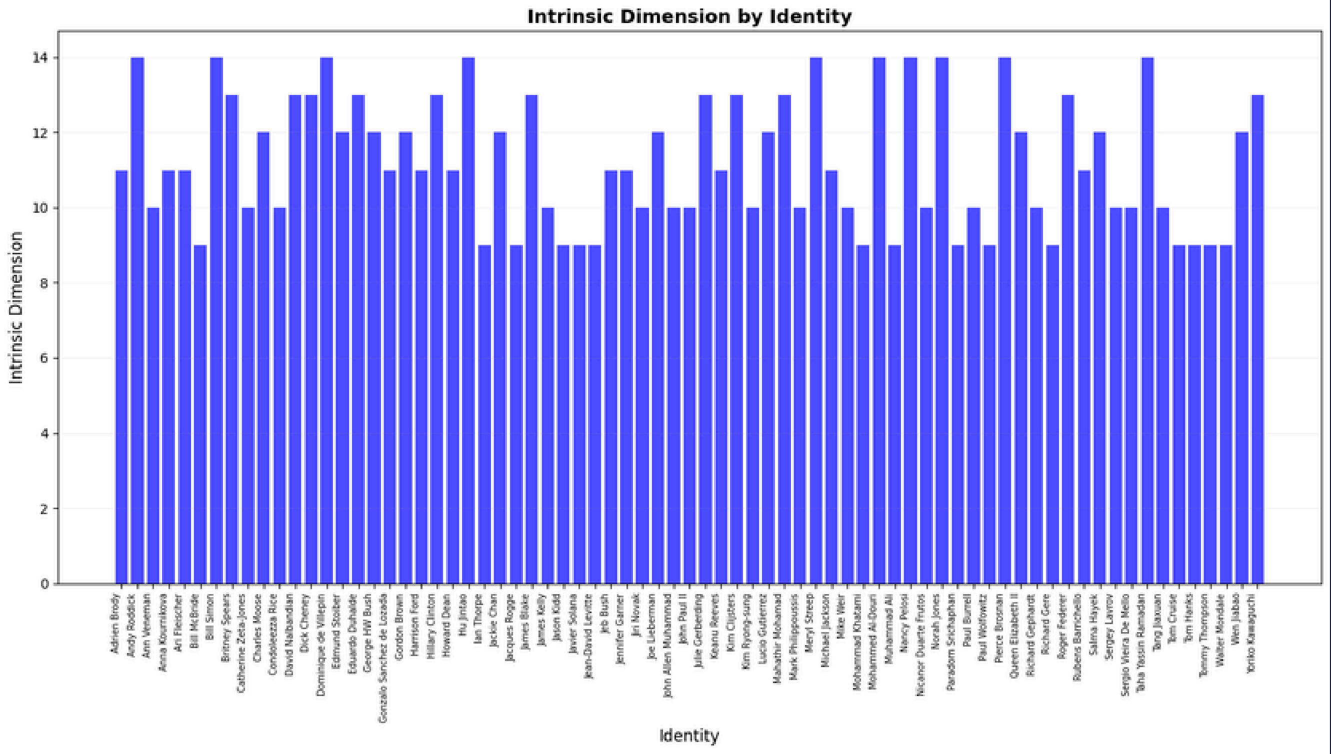
All imgs



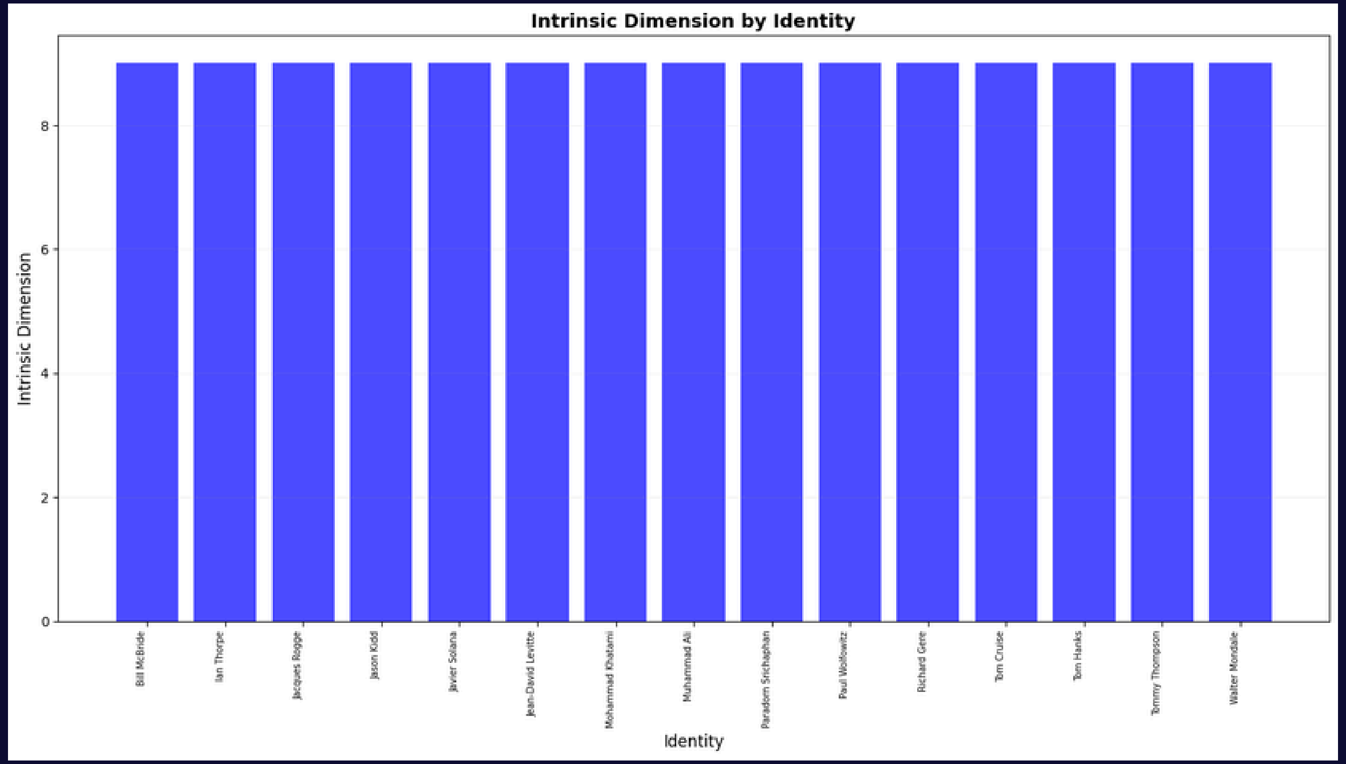
10-25 imgs



10-15 imgs

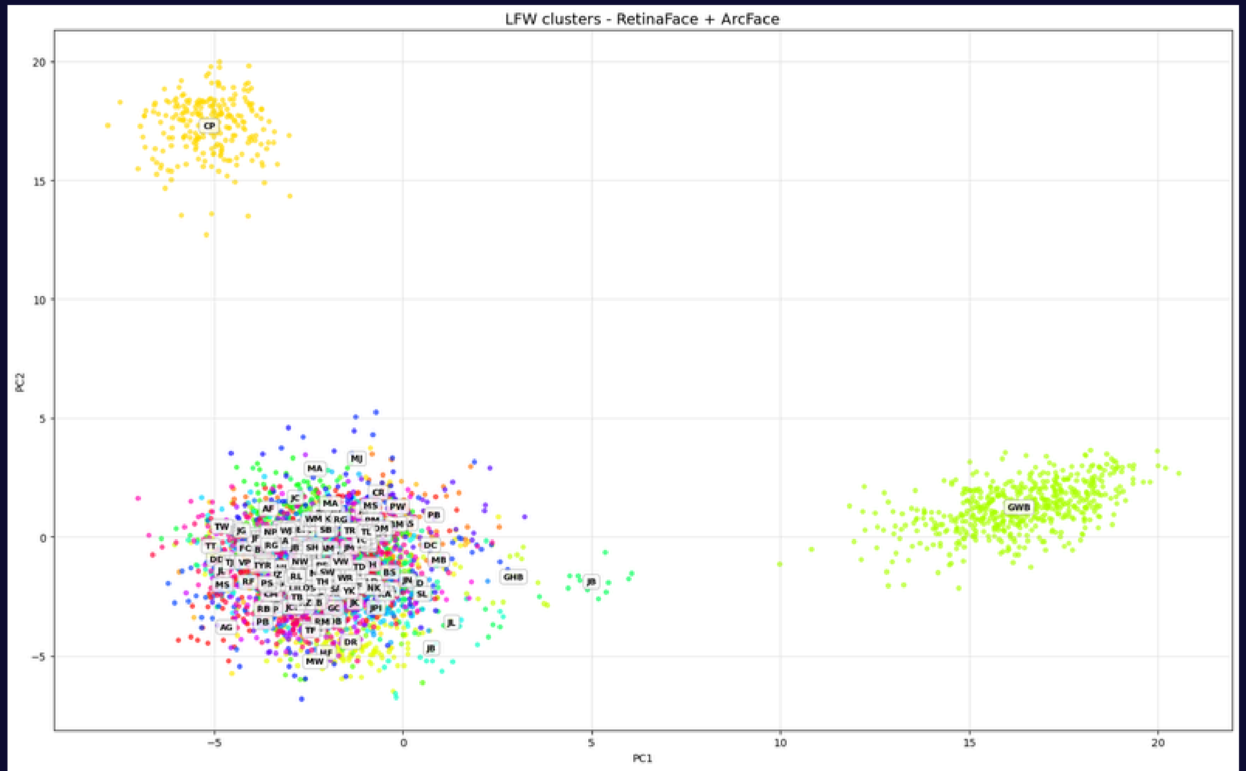


5-10 imgs

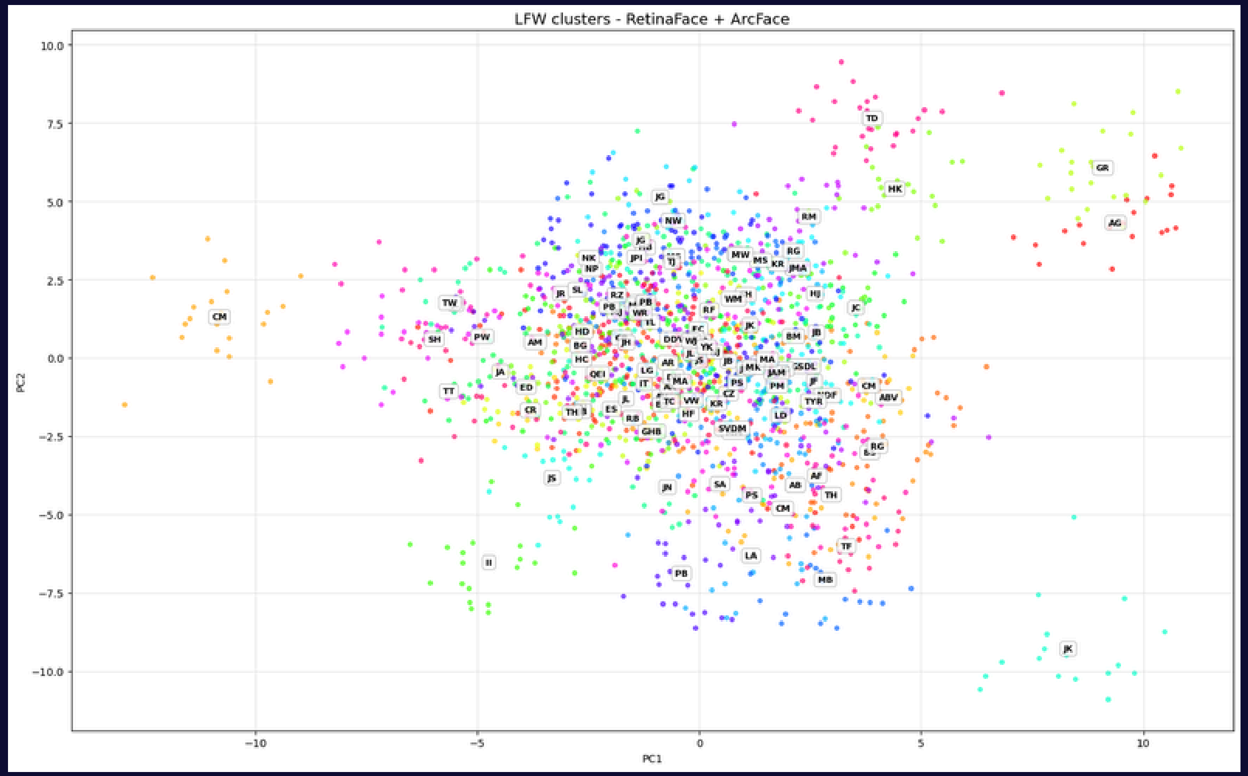


Visualization clusters

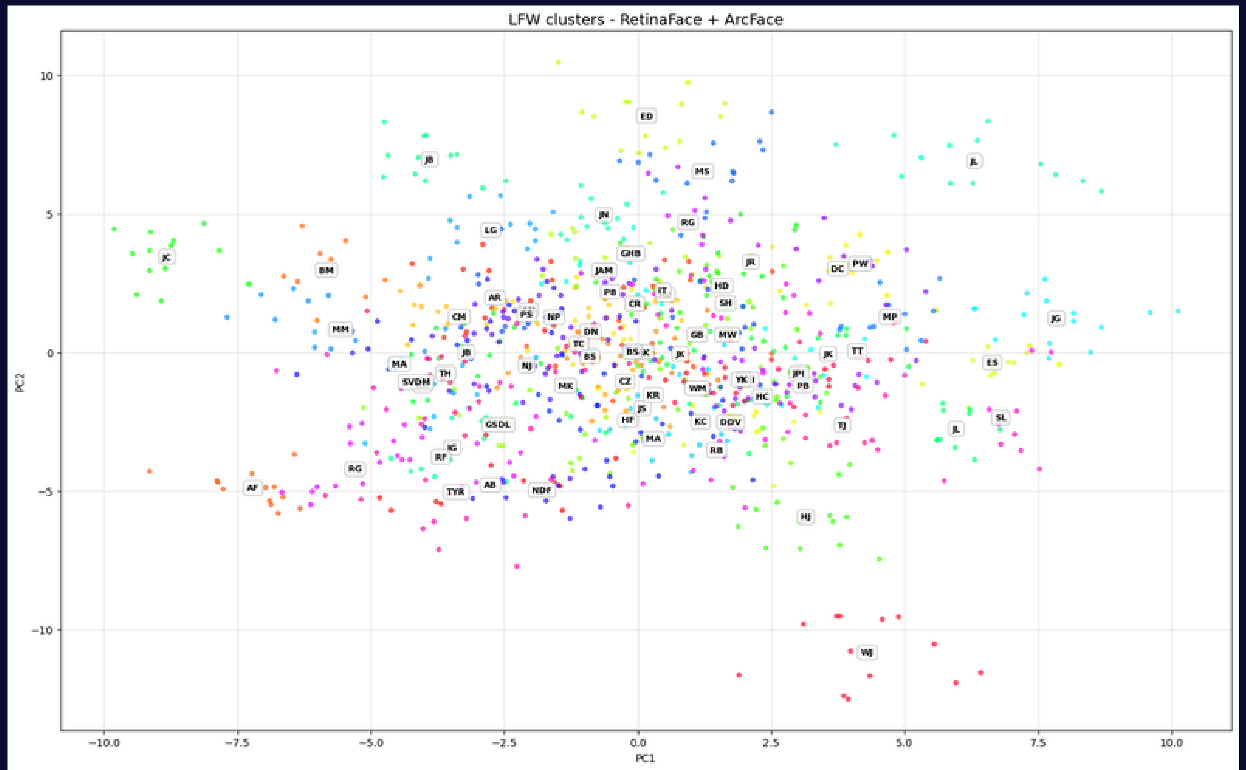
All imgs



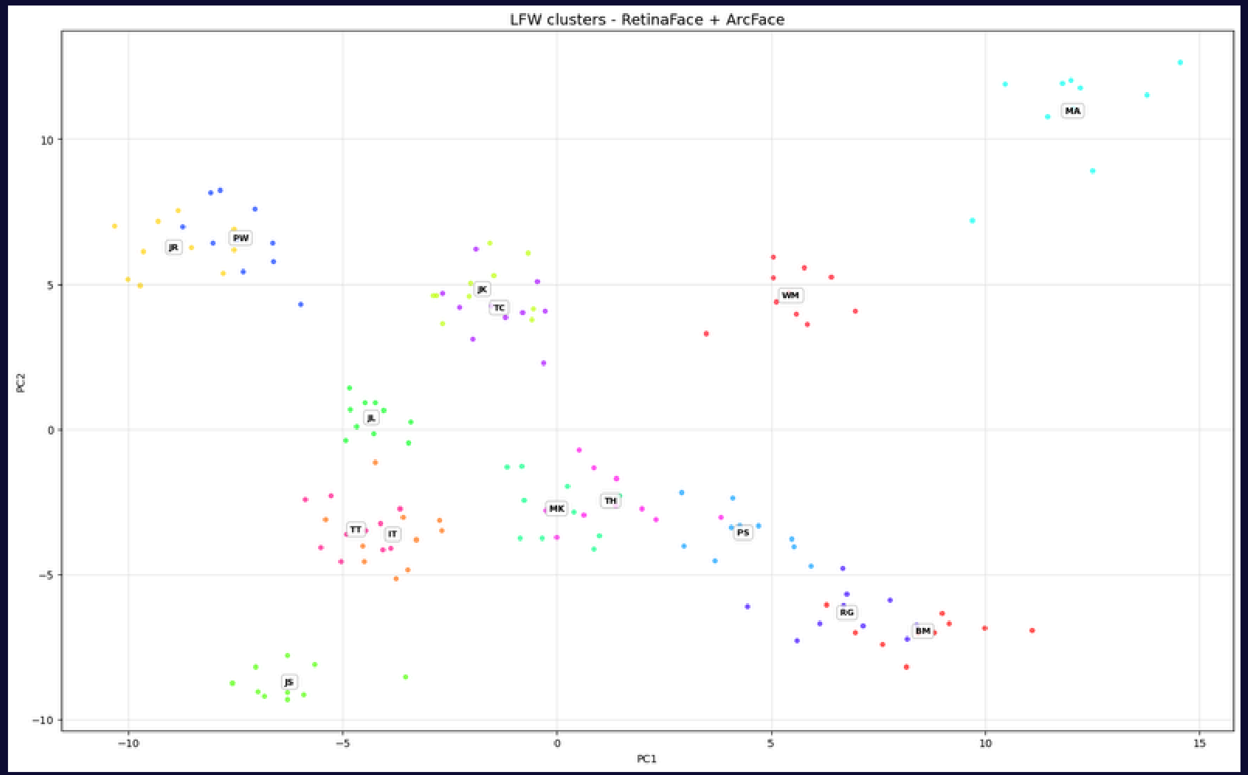
10-25 imgs



10-15 imgs

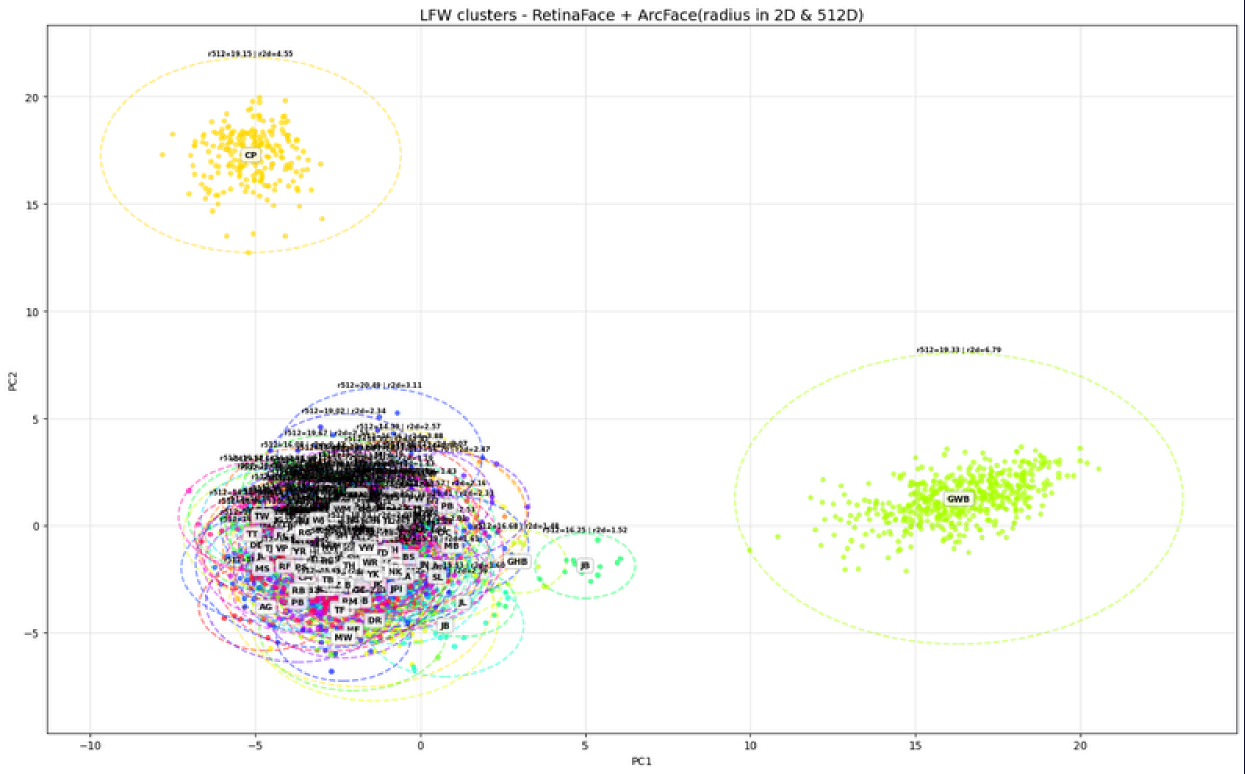


5-10 imgs

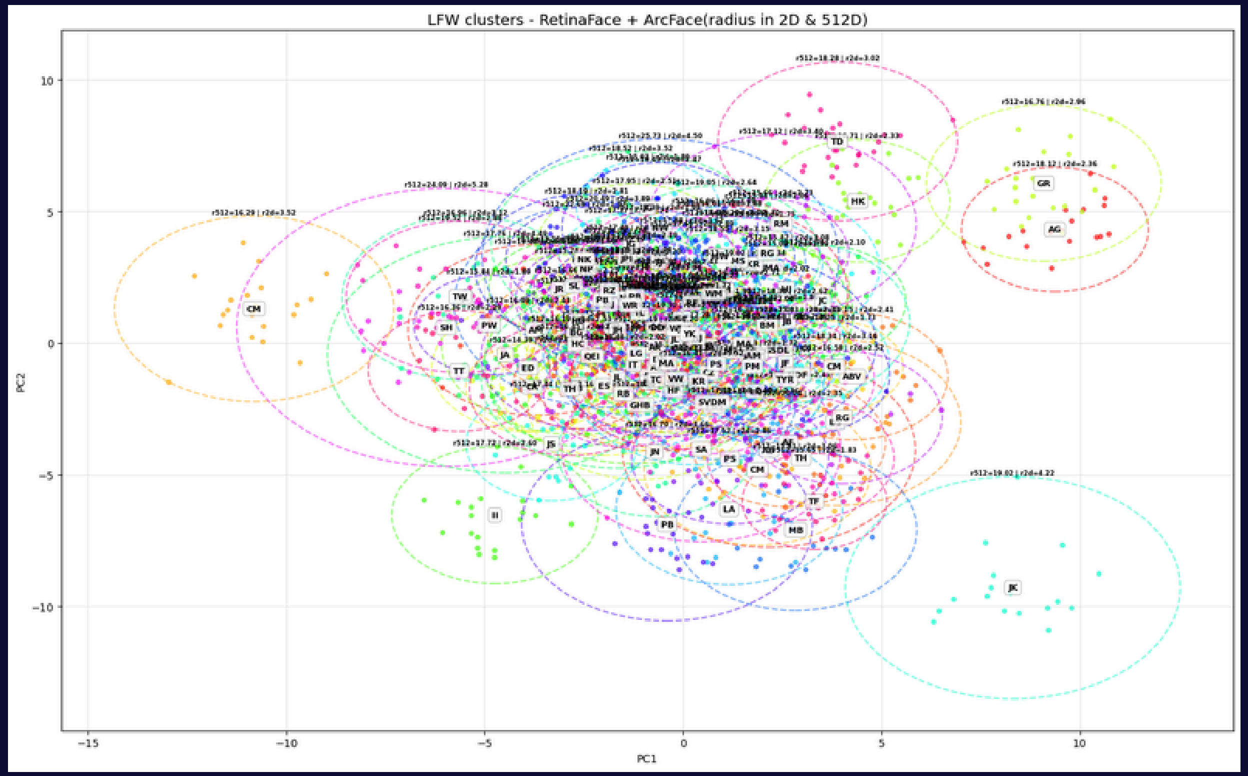


Visualization clusters with radius

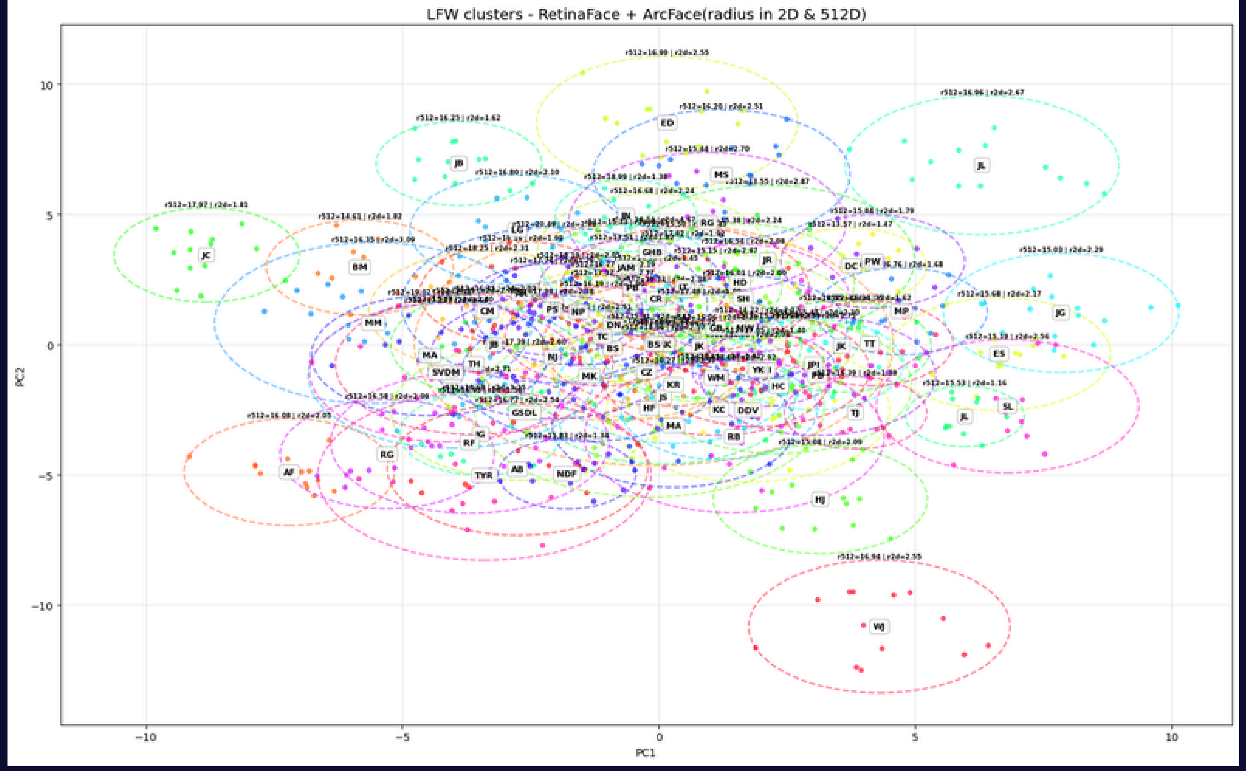
All imgs



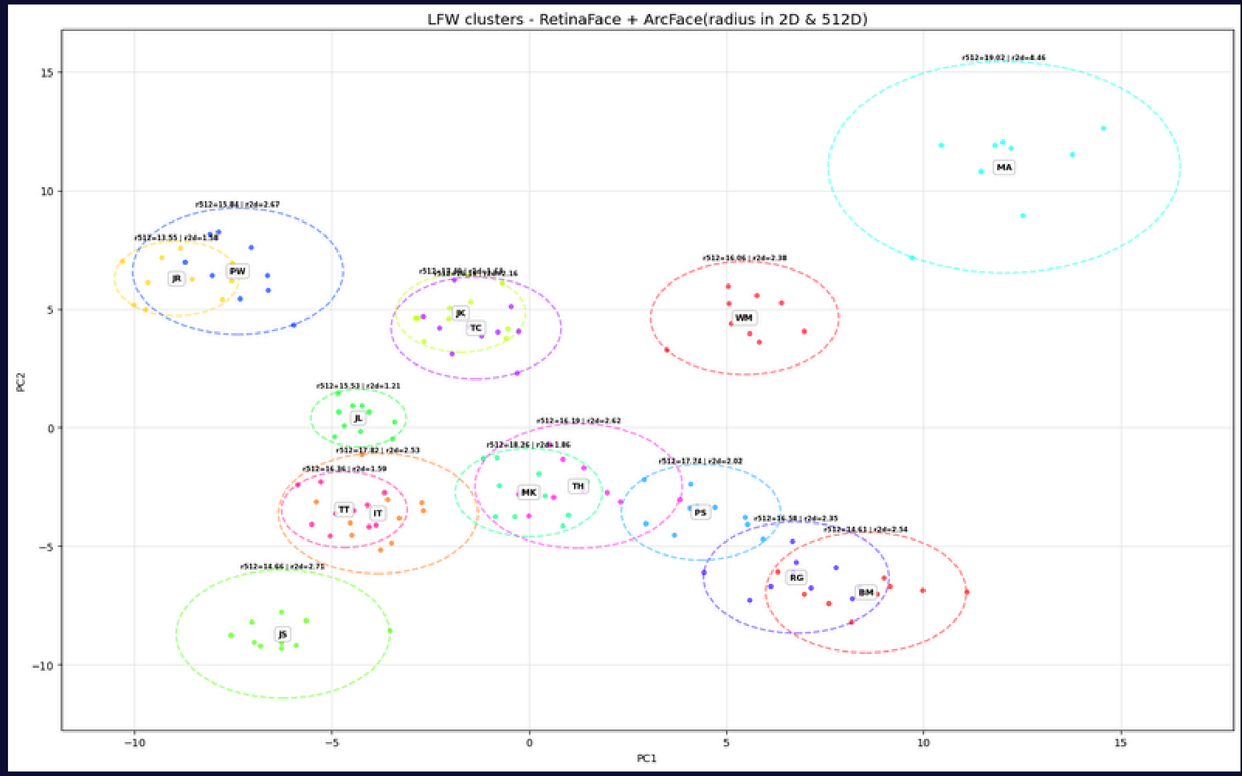
10-25 imgs



10-15 imgs



5-10 imgs



Cosine similarity

All imgs

```
Cosine similarity Abdullah Gul vs Adrien Brody: 0.021794546395540237
Cosine similarity Adrien Brody vs Alejandro Toledo: -0.05306299403309822
Cosine similarity Alejandro Toledo vs Alvaro Uribe: -0.01882879249751568
Cosine similarity Alvaro Uribe vs Amelie Mauresmo: -0.0025038542225956917
Cosine similarity Amelie Mauresmo vs Andre Agassi: -0.07668893039226532
Cosine similarity Andre Agassi vs Andy Roddick: 0.0671813040971756
Cosine similarity Andy Roddick vs Angelina Jolie: -0.022662023082375526
Cosine similarity Angelina Jolie vs Ann Veneman: 0.02324599400162697
Cosine similarity Ann Veneman vs Anna Kournikova: 0.20612077414989471
Cosine similarity Anna Kournikova vs Ari Fleischer: 0.10760828852653503
Cosine similarity Ari Fleischer vs Ariel Sharon: -0.0748133510351181
Cosine similarity Ariel Sharon vs Arnold Schwarzenegger: 0.10506404936313629
Cosine similarity Arnold Schwarzenegger vs Atal Bihari Vajpayee: -0.00485227070748806
Cosine similarity Atal Bihari Vajpayee vs Bill Clinton: -0.09711261093616486
Cosine similarity Bill Clinton vs Bill Gates: 0.07314656674861908
Cosine similarity Bill Gates vs Bill McBride: -0.01738612726330757
Cosine similarity Bill McBride vs Bill Simon: 0.17490625381469727
Cosine similarity Bill Simon vs Britney Spears: 0.06332524120807648
Cosine similarity Britney Spears vs Carlos Menem: -0.028913166373968124
Cosine similarity Carlos Menem vs Carlos Moya: 0.016242824494838715
Cosine similarity Carlos Moya vs Catherine Zeta-Jones: 0.08078894019126892
Cosine similarity Catherine Zeta-Jones vs Charles Moose: -0.007595952600240707
Cosine similarity Charles Moose vs Colin Powell: 0.07687127590179443
Cosine similarity Colin Powell vs Condoleezza Rice: 0.12648215889930725
Cosine similarity Condoleezza Rice vs David Beckham: -0.03039529174566269
...
```

10-25 imgs

```
Cosine similarity Abdullah Gul vs Adrien Brody: 0.021794546395540237
Cosine similarity Adrien Brody vs Amelie Mauresmo: 0.062211066484451294
Cosine similarity Amelie Mauresmo vs Andy Roddick: 0.19560717046260834
Cosine similarity Andy Roddick vs Angelina Jolie: -0.022662023082375526
Cosine similarity Angelina Jolie vs Ann Veneman: 0.02324599400162697
Cosine similarity Ann Veneman vs Anna Kournikova: 0.20612077414989471
Cosine similarity Anna Kournikova vs Ari Fleischer: 0.10760828852653503
Cosine similarity Ari Fleischer vs Atal Bihari Vajpayee: 0.04301653057336807
Cosine similarity Atal Bihari Vajpayee vs Bill Gates: 0.04734659940004349
Cosine similarity Bill Gates vs Bill McBride: -0.01738612726330757
Cosine similarity Bill McBride vs Bill Simon: 0.17490625381469727
Cosine similarity Bill Simon vs Britney Spears: 0.06332524120807648
Cosine similarity Britney Spears vs Carlos Menem: -0.028913166373968124
Cosine similarity Carlos Menem vs Carlos Moya: 0.016242824494838715
Cosine similarity Carlos Moya vs Catherine Zeta-Jones: 0.08078894019126892
Cosine similarity Catherine Zeta-Jones vs Charles Moose: -0.007595952600240707
Cosine similarity Charles Moose vs Condoleezza Rice: -0.02057027630507946
Cosine similarity Condoleezza Rice vs David Nalbandian: 0.0010014306753873825
Cosine similarity David Nalbandian vs Dick Cheney: -0.010200988501310349
Cosine similarity Dick Cheney vs Dominique de Villepin: -0.049509089440107346
Cosine similarity Dominique de Villepin vs Edmund Stoiber: -0.012679949402809143
Cosine similarity Edmund Stoiber vs Eduardo Duhalde: 0.034383971244096756
Cosine similarity Eduardo Duhalde vs Fidel Castro: -0.0697823092341423
Cosine similarity Fidel Castro vs George HW Bush: -0.043985188007354736
Cosine similarity George HW Bush vs George Robertson: 0.016593528911471367
...
```

10-15 imgs

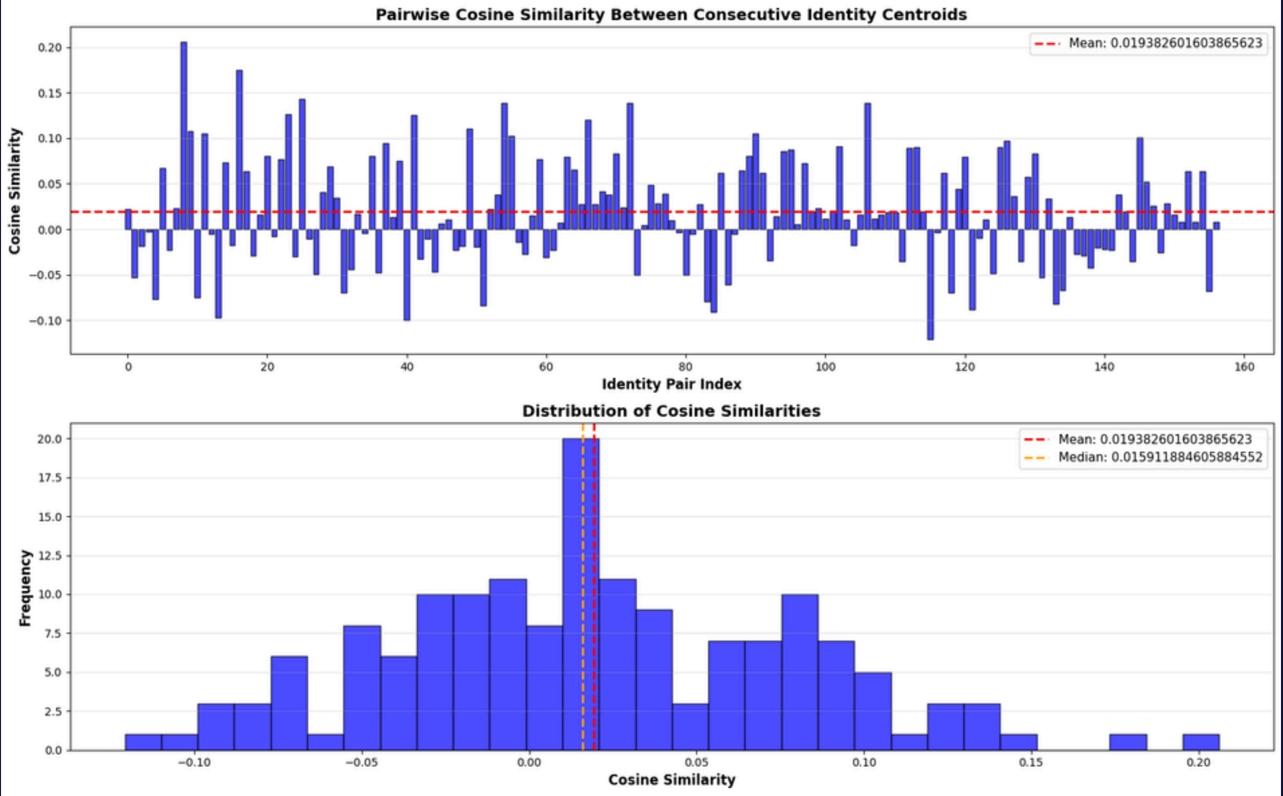
```
Cosine similarity Adrien Brody vs Andy Roddick: 0.012591581791639328
Cosine similarity Andy Roddick vs Ann Veneman: 0.022345319390296936
Cosine similarity Ann Veneman vs Anna Kournikova: 0.20612077414989471
Cosine similarity Anna Kournikova vs Ari Fleischer: 0.10760828852653503
Cosine similarity Ari Fleischer vs Bill McBride: 0.0959300845861435
Cosine similarity Bill McBride vs Bill Simon: 0.17490625381469727
Cosine similarity Bill Simon vs Britney Spears: 0.06332524120807648
Cosine similarity Britney Spears vs Catherine Zeta-Jones: -0.0071835704147815704
Cosine similarity Catherine Zeta-Jones vs Charles Moose: -0.007595952600240707
Cosine similarity Charles Moose vs Condoleezza Rice: -0.02057027630507946
Cosine similarity Condoleezza Rice vs David Nalbandian: 0.0010014306753873825
Cosine similarity David Nalbandian vs Dick Cheney: -0.010200988501310349
Cosine similarity Dick Cheney vs Dominique de Villepin: -0.049509089440107346
Cosine similarity Dominique de Villepin vs Edmund Stoiber: -0.012679949402809143
Cosine similarity Edmund Stoiber vs Eduardo Duhalde: 0.034383971244096756
Cosine similarity Eduardo Duhalde vs George HW Bush: 0.09590218961238861
Cosine similarity George HW Bush vs Gonzalo Sanchez de Lozada: -0.0065382663160562515
Cosine similarity Gonzalo Sanchez de Lozada vs Gordon Brown: 0.012981019914150238
Cosine similarity Gordon Brown vs Harrison Ford: -0.03382911905646324
Cosine similarity Harrison Ford vs Hillary Clinton: 0.005829255096614361
Cosine similarity Hillary Clinton vs Howard Dean: 0.010319516062736511
Cosine similarity Howard Dean vs Hu Jintao: -0.02315746247768402
Cosine similarity Hu Jintao vs Ian Thorpe: -0.03334145247936249
Cosine similarity Ian Thorpe vs Jackie Chan: 0.060595475137233734
Cosine similarity Jackie Chan vs Jacques Rogge: 0.11199718713760376
...
```

5-10 imgs

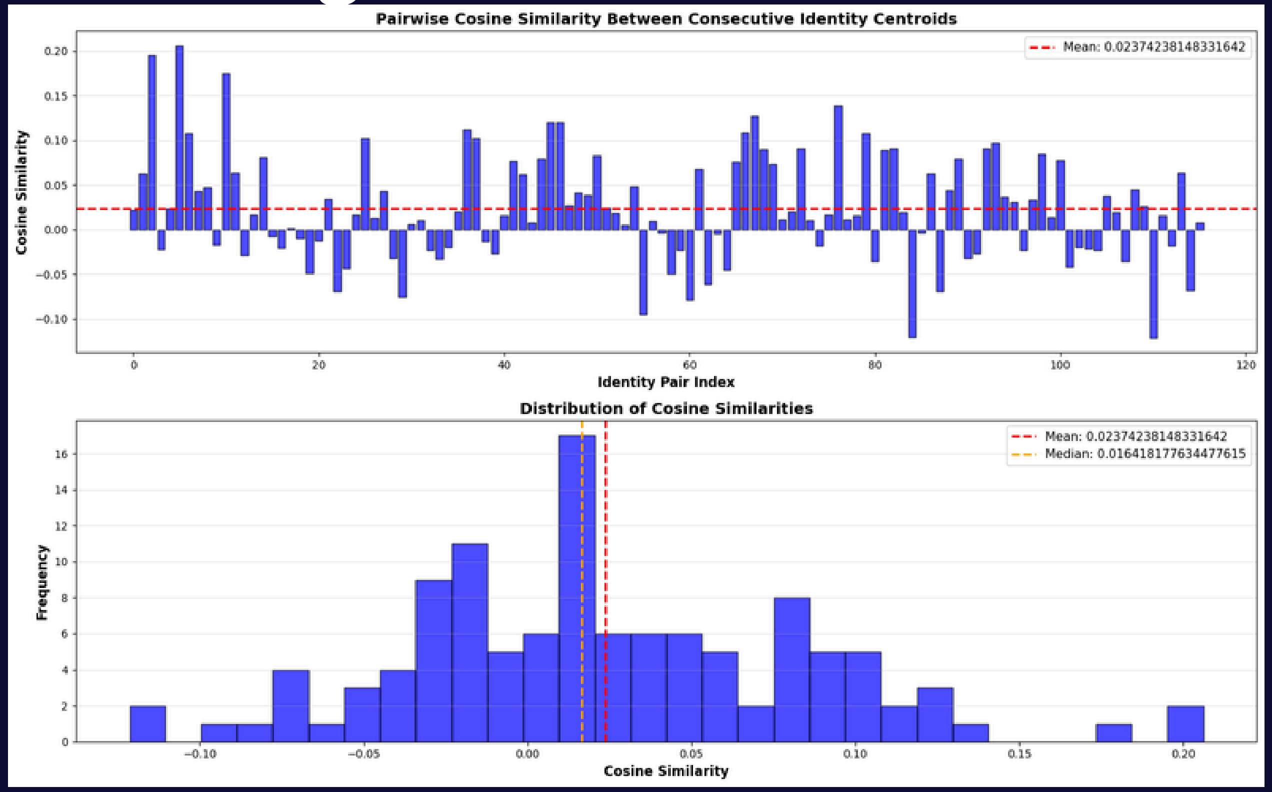
```
Cosine similarity Bill McBride vs Ian Thorpe: 0.03181907534599304
Cosine similarity Ian Thorpe vs Jacques Rogge: 0.04901978373527527
Cosine similarity Jacques Rogge vs Jason Kidd: 0.09661991894245148
Cosine similarity Jason Kidd vs Javier Solana: 0.01521378755569458
Cosine similarity Javier Solana vs Jean-David Levitte: -0.0025644637644290924
Cosine similarity Jean-David Levitte vs Mohammad Khatami: -0.02664436586201191
Cosine similarity Mohammad Khatami vs Muhammad Ali: 0.034930519759655
Cosine similarity Muhammad Ali vs Paradorn Srichaphan: 0.02968042716383934
Cosine similarity Paradorn Srichaphan vs Paul Wolfowitz: -0.11498323082923889
Cosine similarity Paul Wolfowitz vs Richard Gere: -0.1121838241815567
Cosine similarity Richard Gere vs Tom Cruise: 0.09773191064596176
Cosine similarity Tom Cruise vs Tom Hanks: 0.08558108657598495
Cosine similarity Tom Hanks vs Tommy Thompson: 0.08315243571996689
Cosine similarity Tommy Thompson vs Walter Mondale: -0.07688538730144501
```

Cosine similarity distribution and frequency

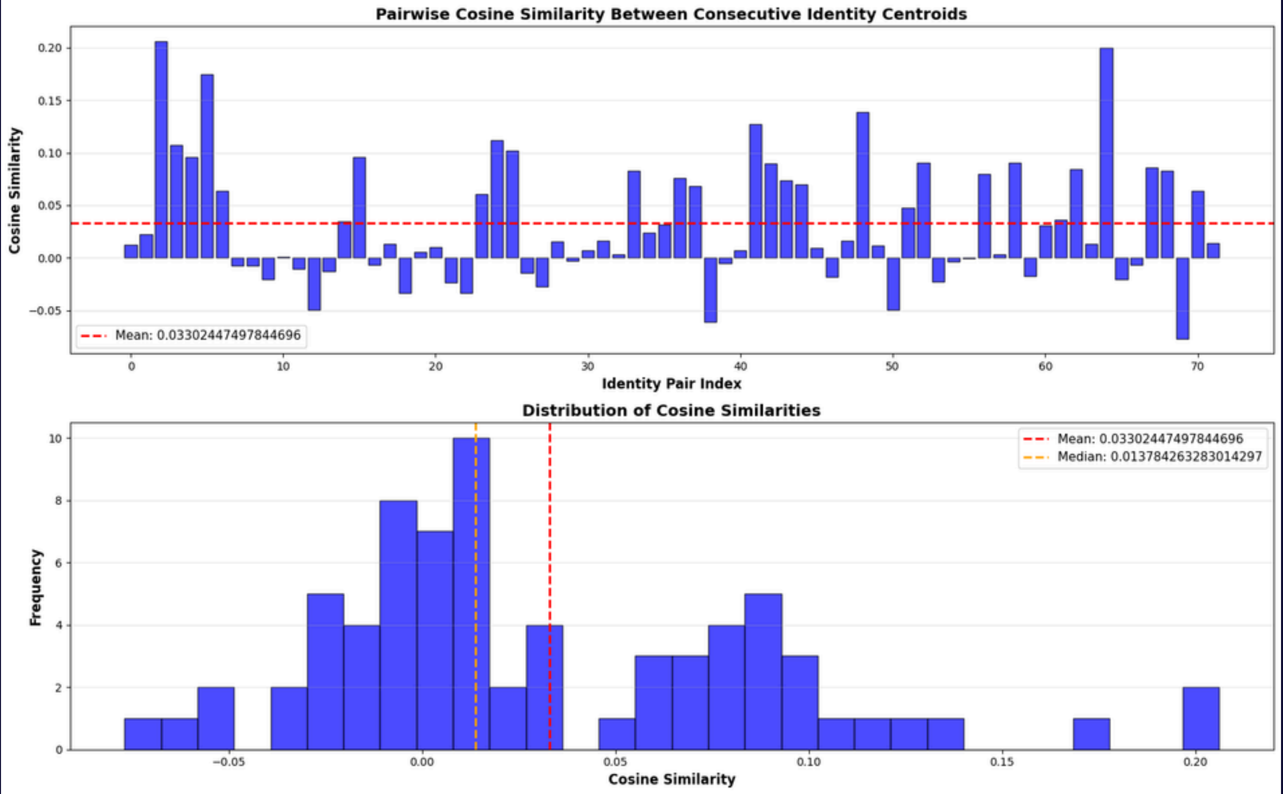
All imgs



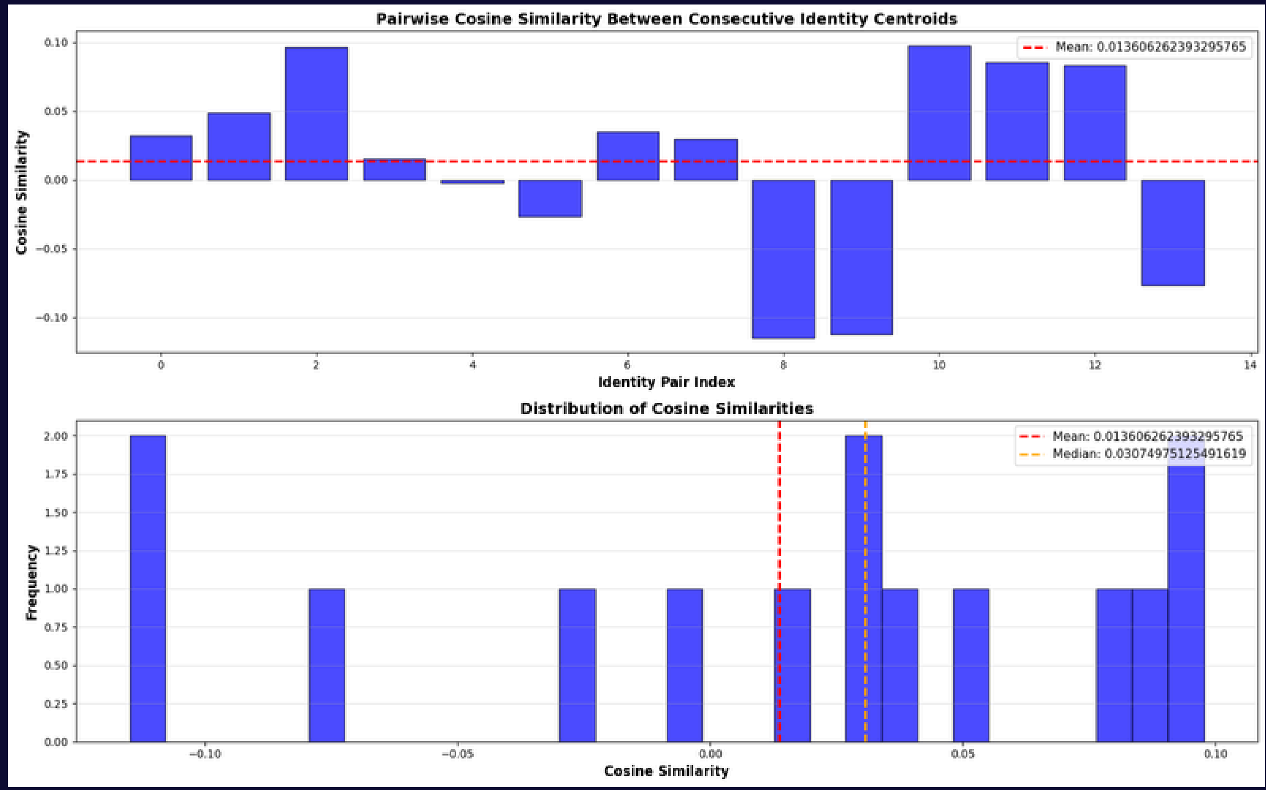
10-25 imgs



10-15 imgs



5-10 imgs



Cosine similarity statistics

All imgs

```
==================================================
COSINE SIMILARITY STATISTICS (Consecutive Pairs):
==================================================
Mean similarity: 0.019382601603865623
Median similarity: 0.015911884605884552
Std deviation: 0.06011653319001198
Min similarity: -0.12082041054964066
Max similarity: 0.20612077414989471
```

10-25 imgs

```
==================================================
COSINE SIMILARITY STATISTICS (Consecutive Pairs):
==================================================
Mean similarity: 0.02374238148331642
Median similarity: 0.016418177634477615
Std deviation: 0.06097012098550797
Min similarity: -0.12145048379898071
Max similarity: 0.20612077414989471
```

10-15 imgs

```
==================================================
COSINE SIMILARITY STATISTICS (Consecutive Pairs):
==================================================
Mean similarity: 0.03302447497844696
Median similarity: 0.013784263283014297
Std deviation: 0.05833731219172478
Min similarity: -0.07688538730144501
Max similarity: 0.20612077414989471
```

5-10 imgs

```
==================================================
COSINE SIMILARITY STATISTICS (Consecutive Pairs):
==================================================
Mean similarity: 0.013606262393295765
Median similarity: 0.03074975125491619
Std deviation: 0.07005900144577026
Min similarity: -0.11498323082923889
Max similarity: 0.09773191064596176
```

Analyze cluster stats: Summary

All imgs

Summary Statistics for Merged DataFrame:

	intrinsic_dimension	radius	dispersion	num_images
count	158.000000	158.000000	158.000000	158.000000
mean	17.632911	17.617338	1.611169	27.367089
std	7.224652	2.188553	0.393341	47.598822
min	9.000000	13.514051	0.703220	10.000000
25%	11.000000	16.367286	1.342523	12.000000
50%	16.000000	17.333834	1.537392	17.000000
75%	24.000000	18.541212	1.803914	26.000000
max	32.000000	29.241322	3.383645	530.000000

10-25 imgs

Summary Statistics for Merged DataFrame:

	intrinsic_dimension	radius	dispersion	num_images
count	117.000000	117.000000	117.000000	117.000000
mean	13.982906	17.190872	1.579089	15.051282
std	4.123070	1.888309	0.385657	4.168532
min	9.000000	13.514051	0.703220	10.000000
25%	10.000000	16.081121	1.295920	11.000000
50%	13.000000	16.936592	1.517158	14.000000
75%	17.000000	18.158503	1.757653	18.000000
max	24.000000	25.731558	2.832243	25.000000

10-15 imgs

Summary Statistics for Merged DataFrame:

	intrinsic_dimension	radius	dispersion	num_images
count	73.000000	73.000000	73.000000	73.000000
mean	11.219178	16.603346	1.499956	12.246575
std	1.734027	1.437990	0.336866	1.754208
min	9.000000	13.514051	0.703220	10.000000
25%	10.000000	15.502258	1.284030	11.000000
50%	11.000000	16.552944	1.426102	12.000000
75%	13.000000	17.493244	1.685850	14.000000
max	14.000000	20.494511	2.647970	15.000000

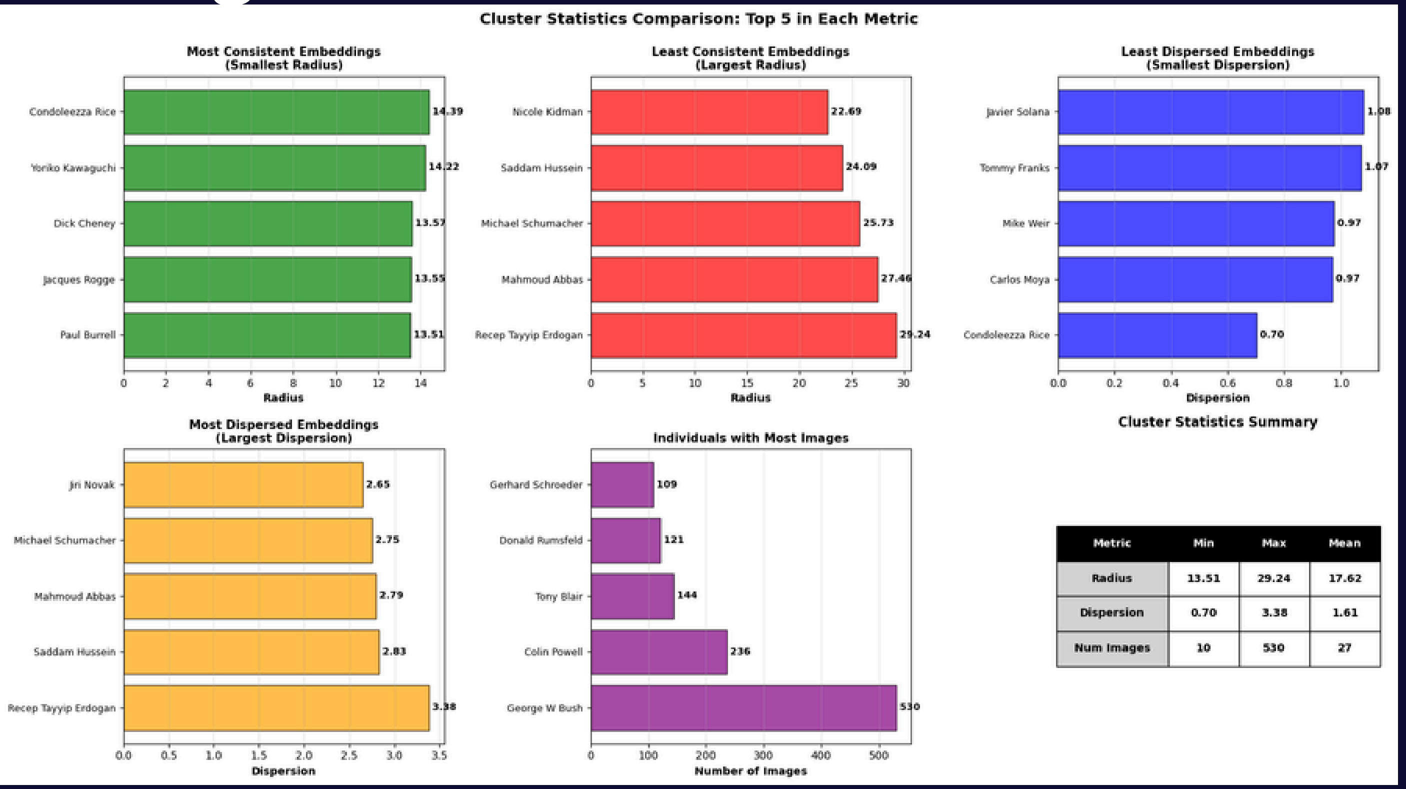
5-10 imgs

Summary Statistics for Merged DataFrame:

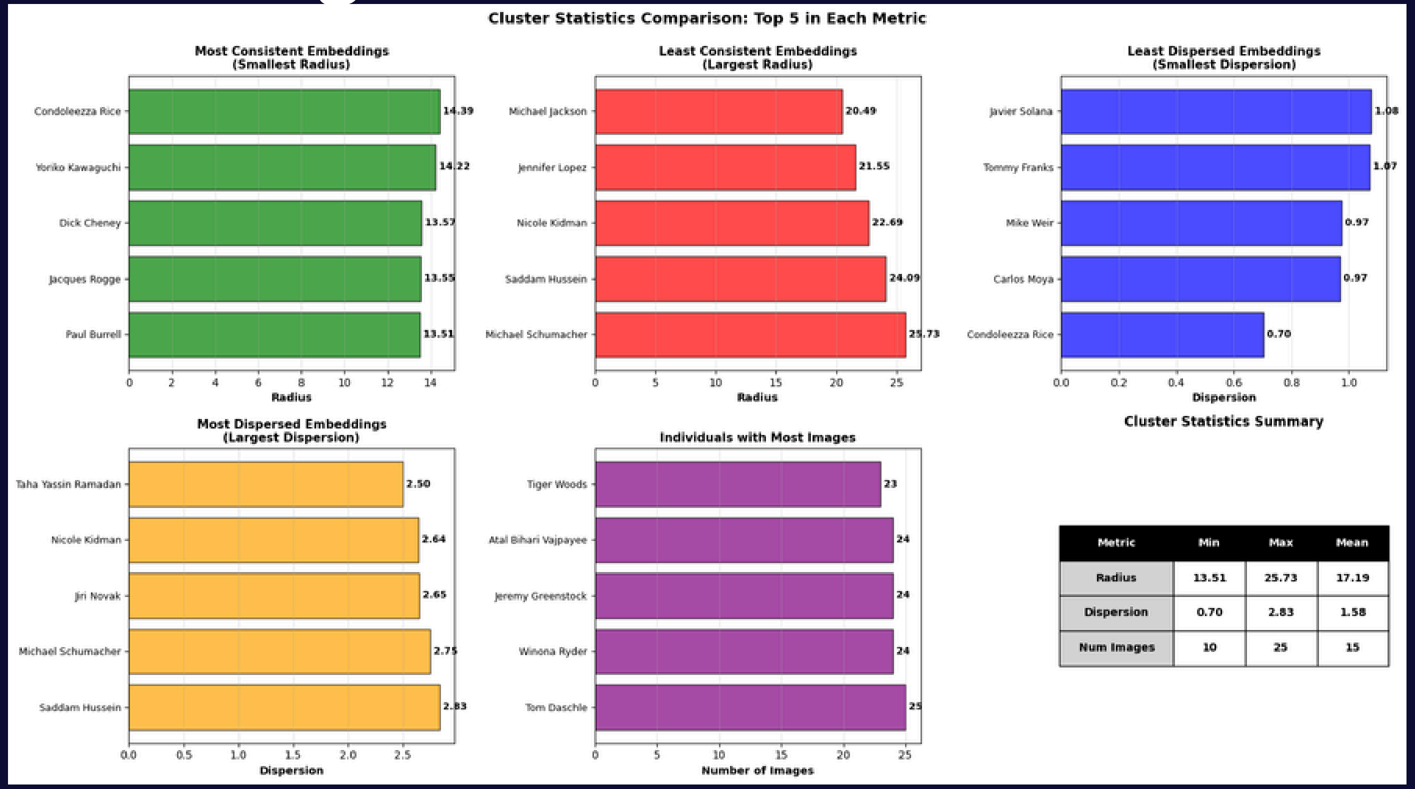
	intrinsic_dimension	radius	dispersion	num_images
count	15.0	15.000000	15.000000	15.0
mean	9.0	16.393955	1.523440	10.0
std	0.0	1.486666	0.272851	0.0
min	9.0	13.552886	1.079403	10.0
25%	9.0	15.686193	1.345187	10.0
50%	9.0	16.191816	1.496330	10.0
75%	9.0	17.615626	1.787171	10.0
max	9.0	19.016243	1.922151	10.0

Analyze cluster stats: Top10 radius, dist, n imgs

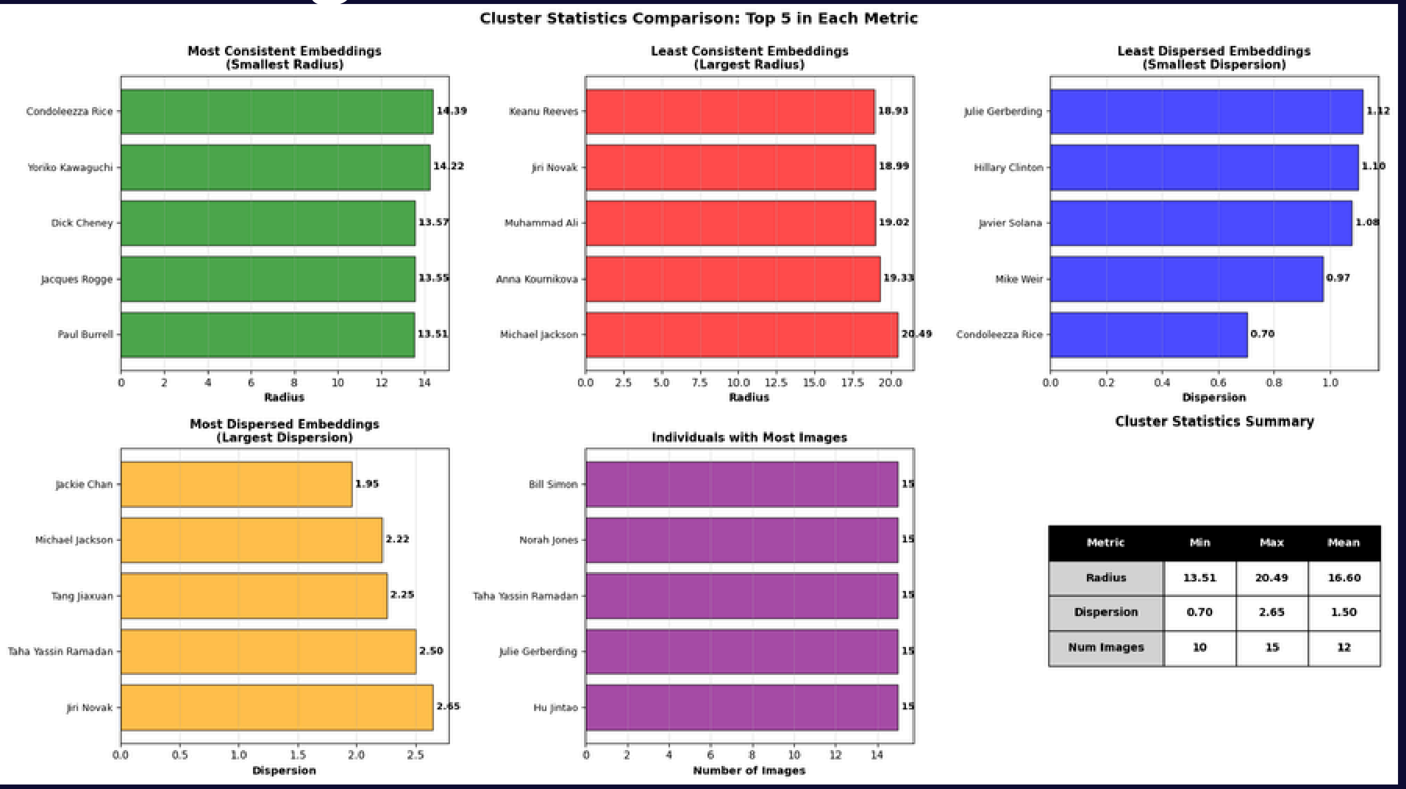
All imgs



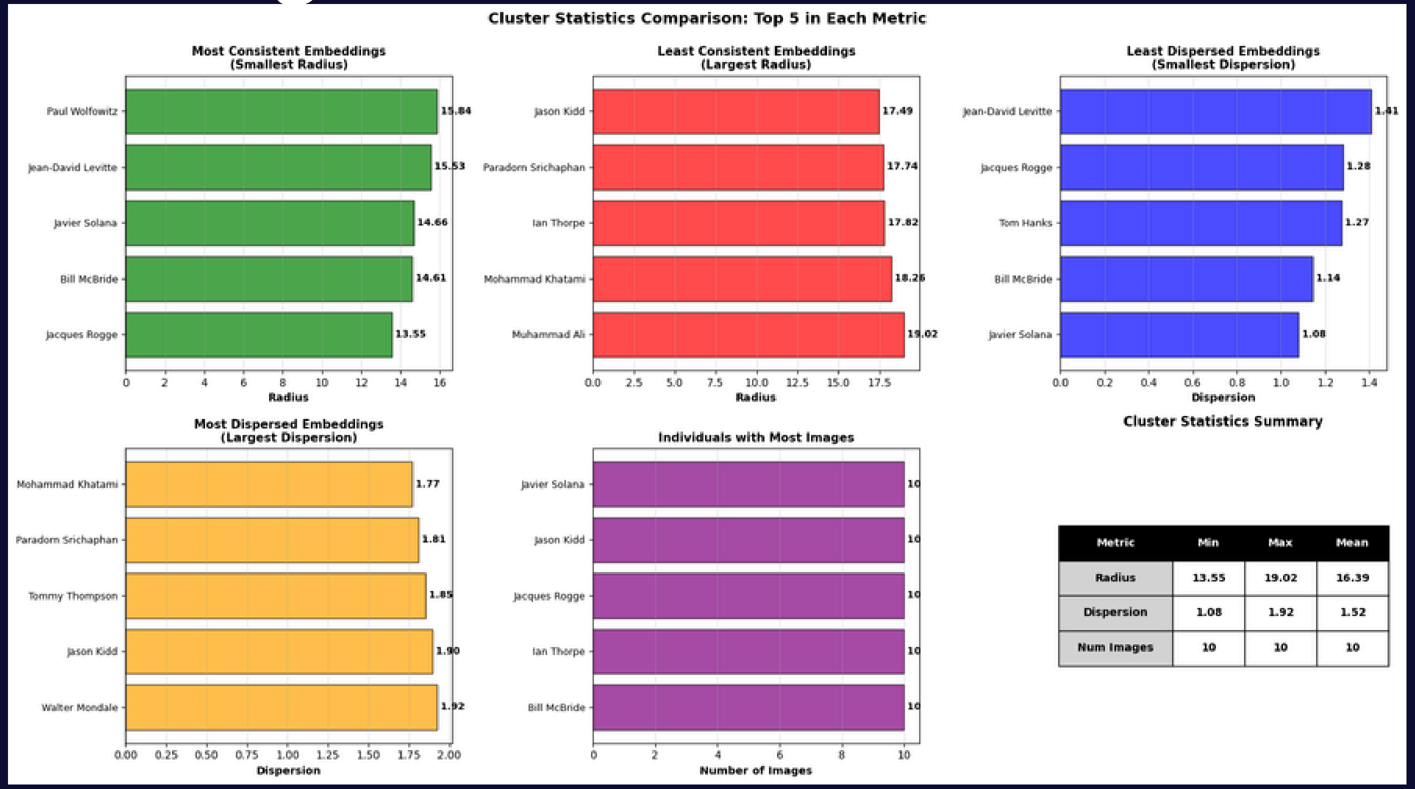
10-25 imgs



10-15 imgs

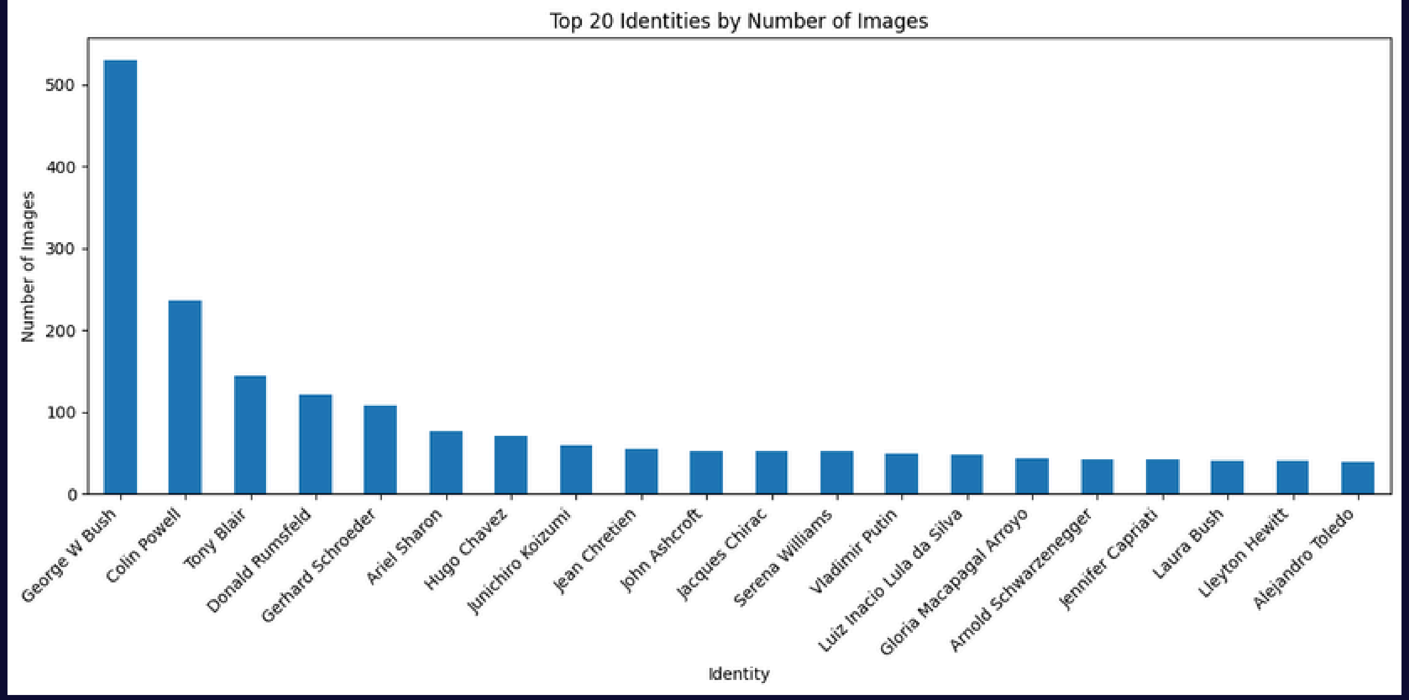


5-10 imgs

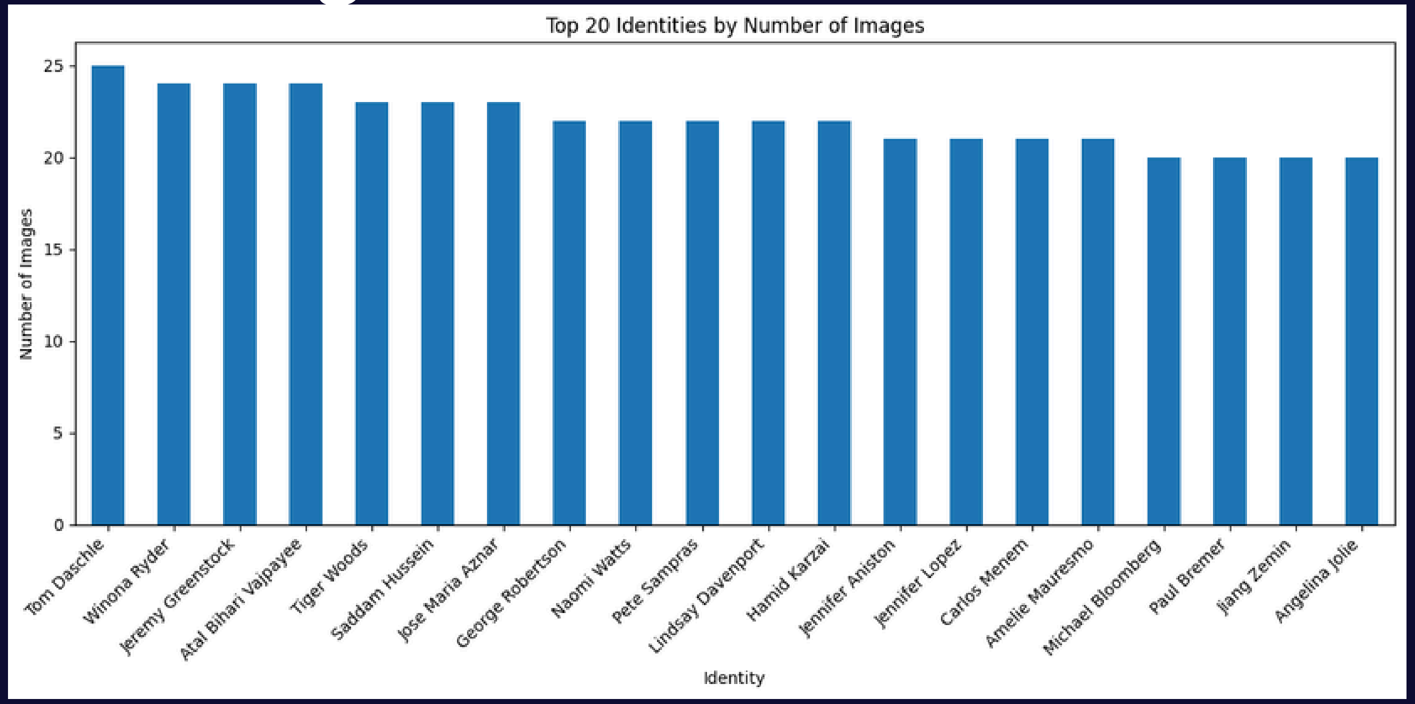


Analyze cluster stats: Top20 N imgs

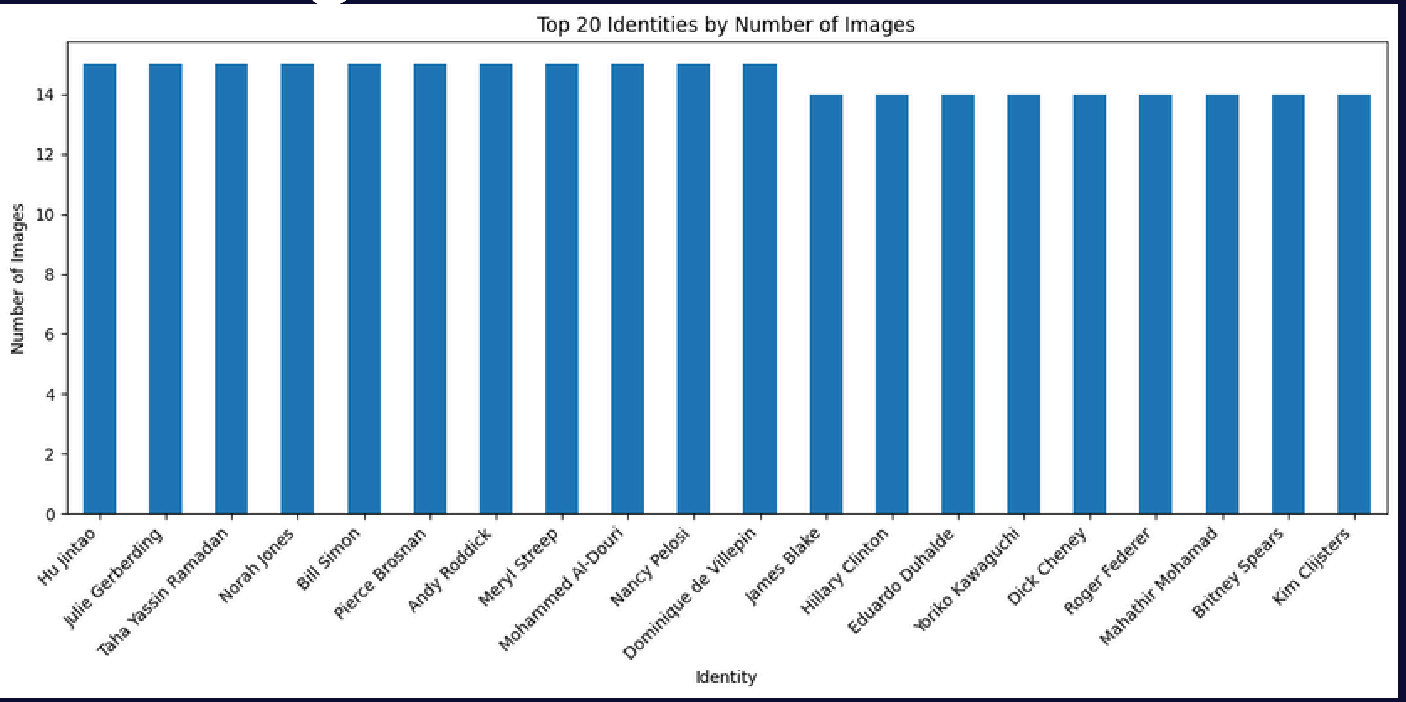
All imgs



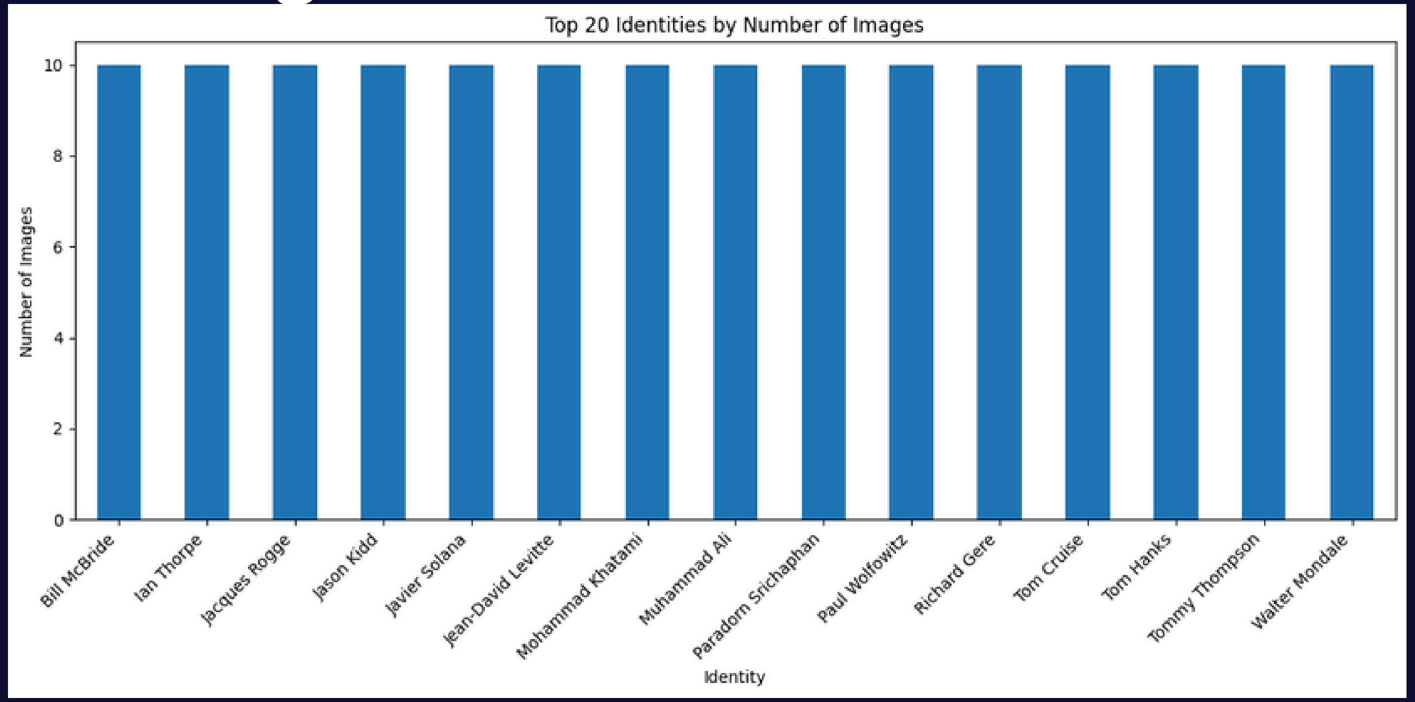
10-25 imgs



10-15 imgs

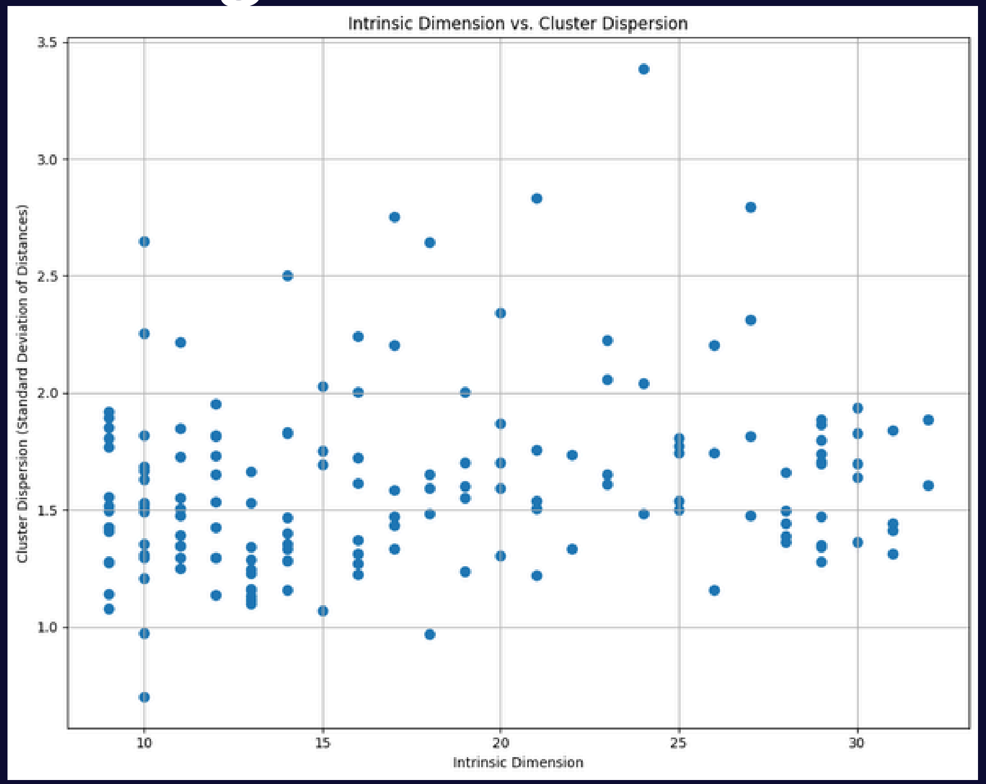


5-10 imgs

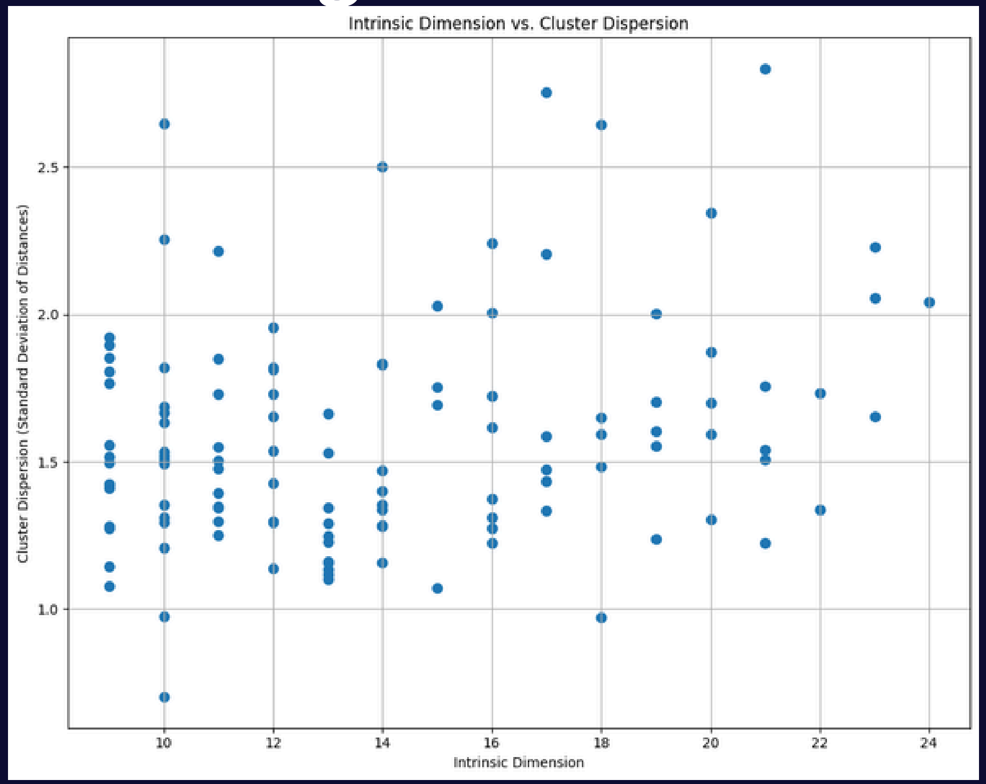


Scatter Plot: Intrinsic Dimension vs. Cluster Dispersion

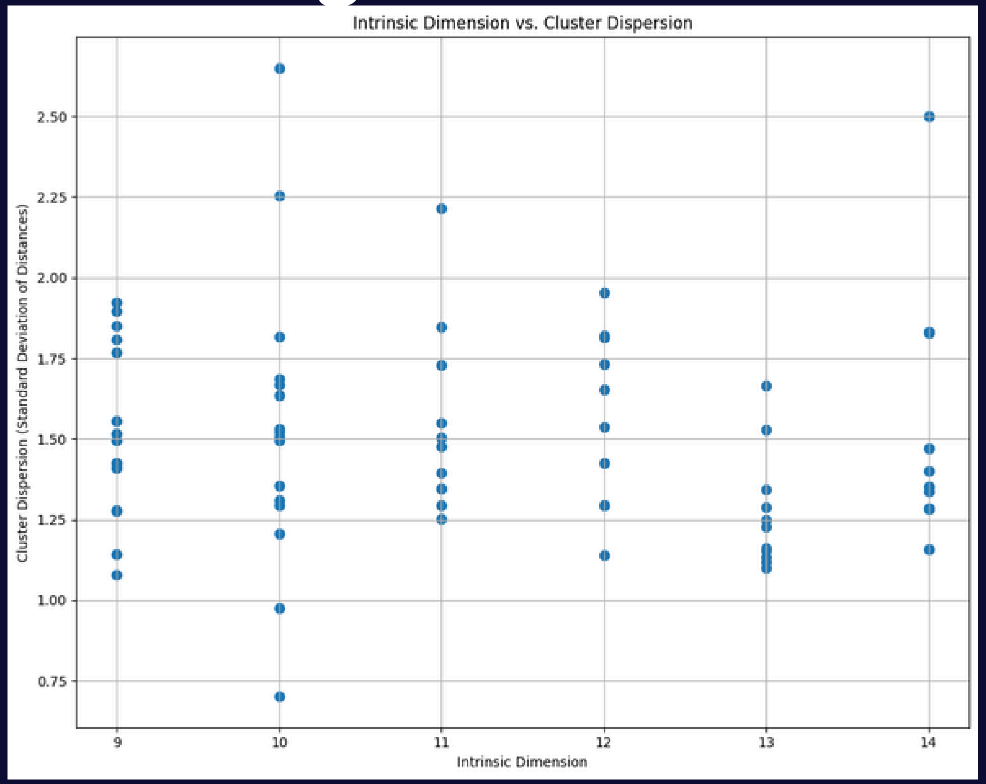
All imgs



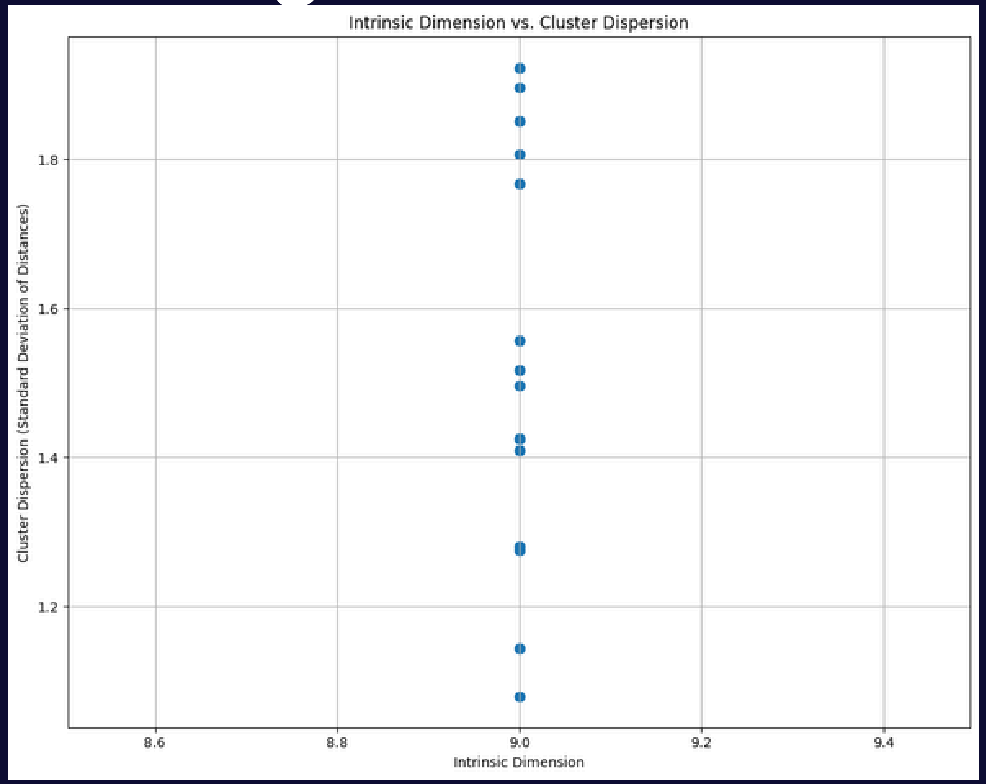
10-25 imgs



10-15 imgs

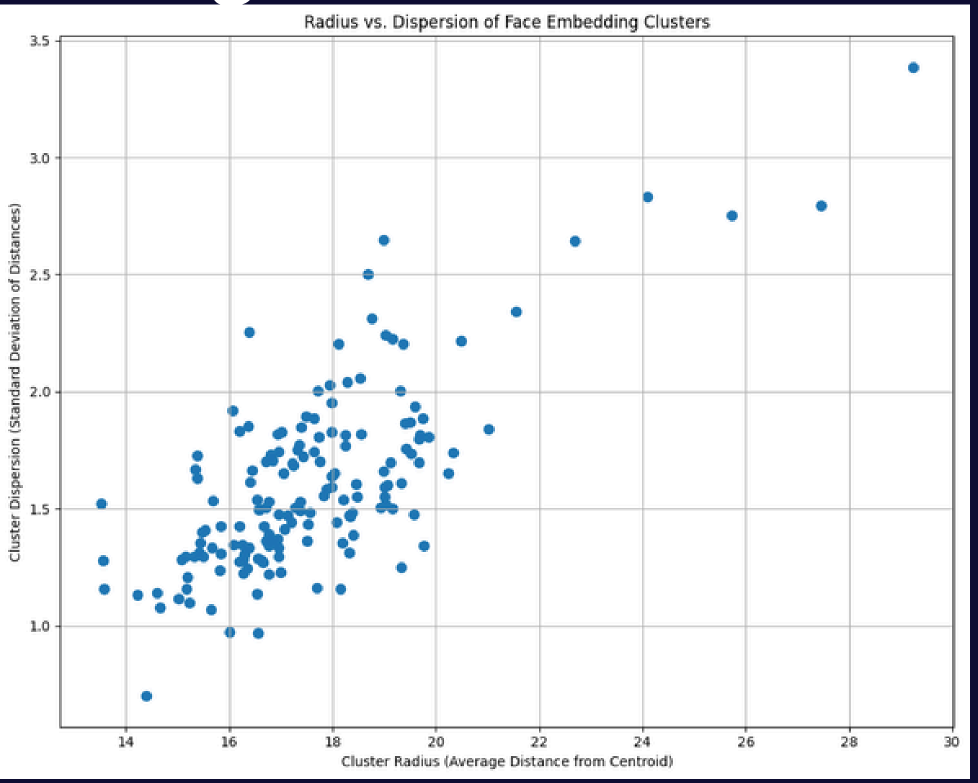


5-10 imgs

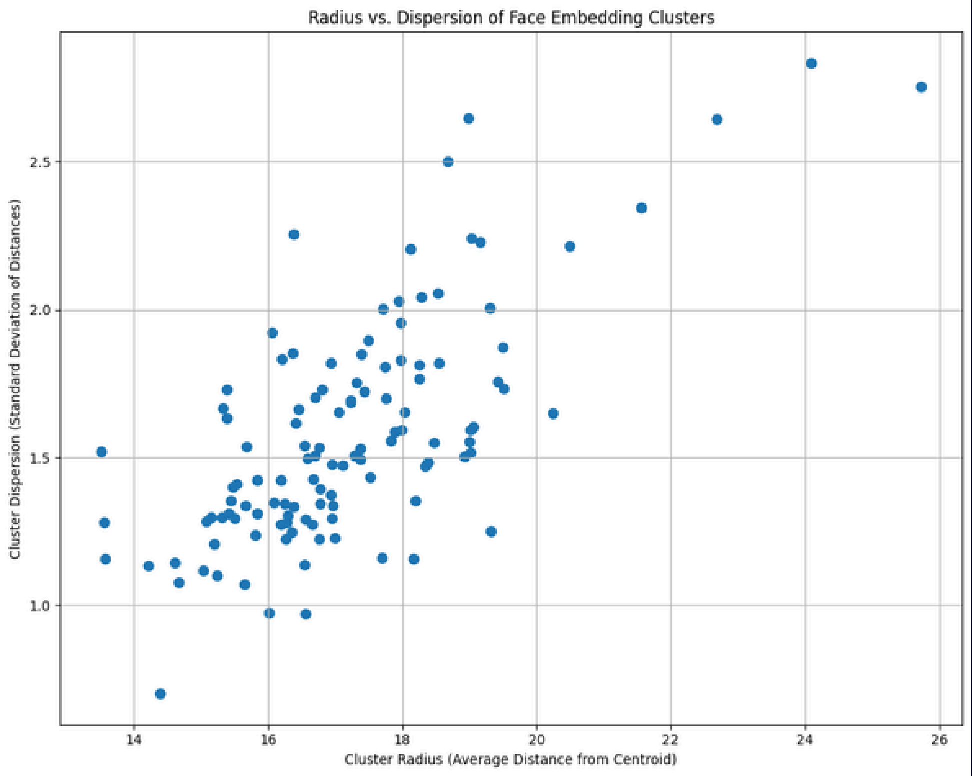


Scatter Plot: Radius vs Dispersion

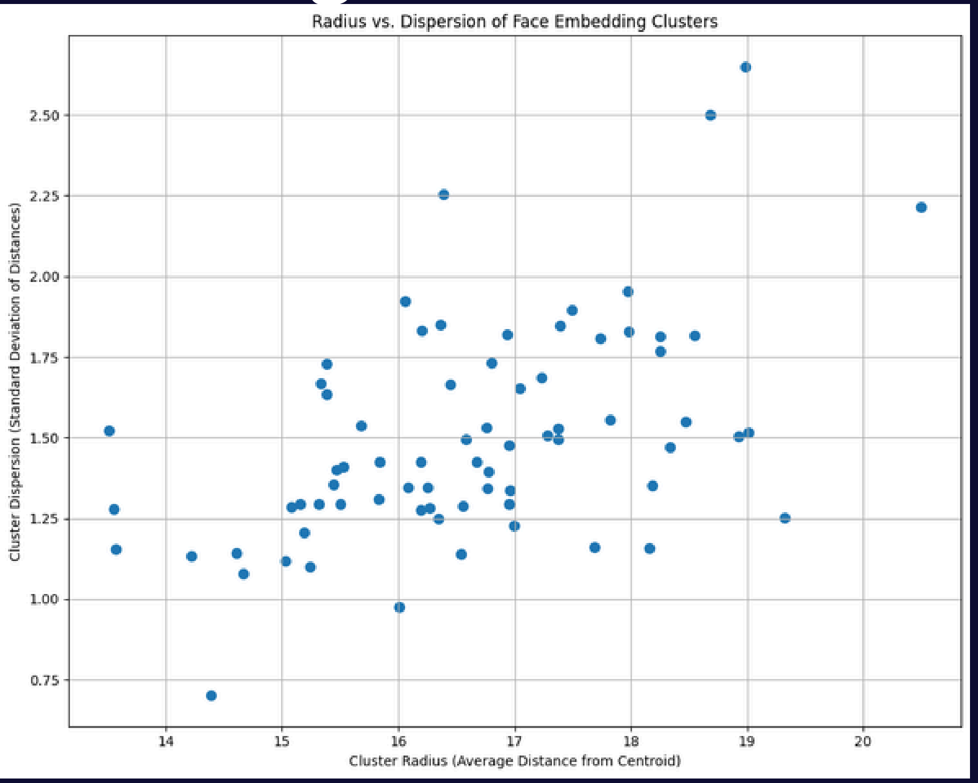
All imgs



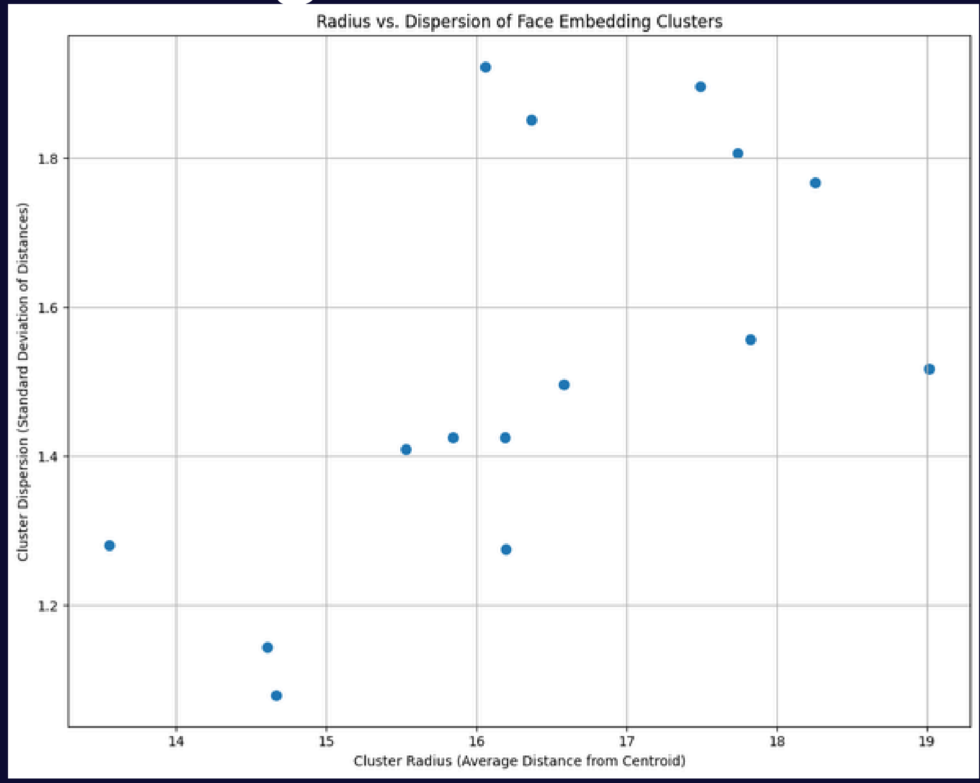
10-25 imgs



10-15 imgs



5-10 imgs



Intrinsic Dimension Summary

All imgs

```
Descriptive Statistics for Intrinsic Dimensionality:
count    158.000000
mean      17.632911
std        7.224652
min        9.000000
25%       11.000000
50%       16.000000
75%       24.000000
max       32.000000
Name: intrinsic_dimension, dtype: float64
```

10-25 imgs

```
Descriptive Statistics for Intrinsic Dimensionality:
count    117.000000
mean      13.982906
std        4.123070
min        9.000000
25%       10.000000
50%       13.000000
75%       17.000000
max       24.000000
Name: intrinsic_dimension, dtype: float64
```

10-15 imgs

```
Descriptive Statistics for Intrinsic Dimensionality:
count    73.000000
mean     11.219178
std       1.734027
min       9.000000
25%      10.000000
50%      11.000000
75%      13.000000
max      14.000000
Name: intrinsic dimension, dtype: float64
```

5-10 imgs

```
Descriptive Statistics for Intrinsic Dimensionality:
count    15.0
mean      9.0
std       0.0
min       9.0
25%       9.0
50%       9.0
75%       9.0
max       9.0
Name: intrinsic_dimension, dtype: float64
```

Intrinsic Dimension High/Low

All imgs

Identities with the 10 highest intrinsic dimensions:

	intrinsic_dimension
Laura Bush	32
John Ashcroft	32
Tom Ridge	31
Gloria Macapagal Arroyo	31
Hugo Chavez	31
Arnold Schwarzenegger	31
Luiz Inacio Lula da Silva	30
Andre Agassi	30
Jennifer Capriati	30
Vladimir Putin	30

Identities with the 10 lowest intrinsic dimensions:

	intrinsic_dimension
Muhammad Ali	9
Jason Kidd	9
Javier Solana	9
Ian Thorpe	9
Jean-David Levitte	9
Mohammad Khatami	9
Paradorn Srichaphan	9
Paul Wolfowitz	9
Richard Gere	9
Bill McBride	9

10-25 imgs

Identities with the 10 highest intrinsic dimensions:

	intrinsic_dimension
Tom Daschle	24
Jeremy Greenstock	23
Winona Ryder	23
Atal Bihari Vajpayee	23
Jose Maria Aznar	22
Tiger Woods	22
Hamid Karzai	21
Lindsay Davenport	21
George Robertson	21
Saddam Hussein	21

Identities with the 10 lowest intrinsic dimensions:

	intrinsic_dimension
Jean-David Levitte	9
Paradorn Srichaphan	9
Muhammad Ali	9
Mohammad Khatami	9
Richard Gere	9
Javier Solana	9
Jason Kidd	9
Jacques Rogge	9
Ian Thorpe	9
Tom Cruise	9

10-15 imgs

Identities with the 10 highest intrinsic dimensions:

	intrinsic_dimension
Pierce Brosnan	14
Dominique de Villepin	14
Meryl Streep	14
Mohammed Al-Douri	14
Hu Jintao	14
Nancy Pelosi	14
Norah Jones	14
Andy Roddick	14
Bill Simon	14
Taha Yassin Ramadan	14

Identities with the 10 lowest intrinsic dimensions:

	intrinsic_dimension
Muhammad Ali	9
Walter Mondale	9
Jean-David Levitte	9
Tommy Thompson	9
Tom Hanks	9
Bill McBride	9
Tom Cruise	9
Javier Solana	9
Jason Kidd	9
Mohammad Khatami	9

5-10 imgs

Identities with the 10 highest intrinsic dimensions:

	intrinsic_dimension
Bill McBride	9
Ian Thorpe	9
Jacques Rogge	9
Jason Kidd	9
Javier Solana	9
Jean-David Levitte	9
Mohammad Khatami	9
Muhammad Ali	9
Paradorn Srichaphan	9
Paul Wolfowitz	9

Identities with the 10 lowest intrinsic dimensions:

	intrinsic_dimension
Bill McBride	9
Ian Thorpe	9
Jacques Rogge	9
Jason Kidd	9
Javier Solana	9
Jean-David Levitte	9
Mohammad Khatami	9
Muhammad Ali	9
Paradorn Srichaphan	9
Paul Wolfowitz	9

Intrinsic Dimension Top10

All imgs

Top 10 Identities with Highest Intrinsic Dimensions

Identity	Intrinsic Dim	Radius	Dispersion	Num Images
John Ashcroft	32	17.65	1.89	53
Laura Bush	32	18.46	1.61	41
Arnold Schwarzenegger	31	21.02	1.84	42
Gloria Macapagal Arroyo	31	18.31	1.31	44
Hugo Chavez	31	18.07	1.44	71
Tom Ridge	31	17.06	1.42	33
Andre Agassi	30	17.51	1.36	36
Ariel Sharon	30	17.01	1.83	77
Jennifer Capriati	30	19.60	1.93	42
Luiz Inacio Lula da Silva	30	17.98	1.64	48

Cluster Statistics Summary

Metric	Max	Min	Mean
Radius (512D)	29.24	13.51	17.62
Dispersion	3.38	0.70	1.61
Num Images	530	10	27

10-25 imgs

Top 10 Identities with Highest Intrinsic Dimensions

Identity	Intrinsic Dim	Radius	Dispersion	Num Images
Tom Daschle	24	18.28	2.04	25
Atal Bihari Vajpayee	23	19.15	2.23	24
Jeremy Greenstock	23	18.52	2.06	24
Winona Ryder	23	18.03	1.65	24
Jose Maria Aznar	22	15.66	1.34	23
Tiger Woods	22	19.52	1.73	23
George Robertson	21	16.76	1.22	22
Hamid Karzai	21	16.71	1.51	22
Lindsay Davenport	21	16.54	1.54	22
Naomi Watts	21	19.43	1.76	22

Cluster Statistics Summary

Metric	Max	Min	Mean
Radius (512D)	25.73	13.51	17.19
Dispersion	2.83	0.70	1.58
Num Images	25	10	15

10-15 imgs

Top 10 Identities with Highest Intrinsic Dimensions

Identity	Intrinsic Dim	Radius	Dispersion	Num Images
Andy Roddick	14	18.16	1.16	15
Bill Simon	14	18.34	1.47	15
Dominique de Villepin	14	16.96	1.34	15
Hu Jintao	14	15.08	1.28	15
Meryl Streep	14	16.20	1.83	15
Mohammed Al-Douri	14	16.27	1.28	15
Nancy Pelosi	14	18.19	1.35	15
Norah Jones	14	17.98	1.83	15
Pierce Brosnan	14	15.47	1.40	15
Taha Yassin Ramadan	14	18.68	2.50	15

Cluster Statistics Summary

Metric	Max	Min	Mean
Radius (512D)	20.49	13.51	16.60
Dispersion	2.65	0.70	1.50
Num Images	15	10	12

5-10 imgs

Top 10 Identities with Highest Intrinsic Dimensions

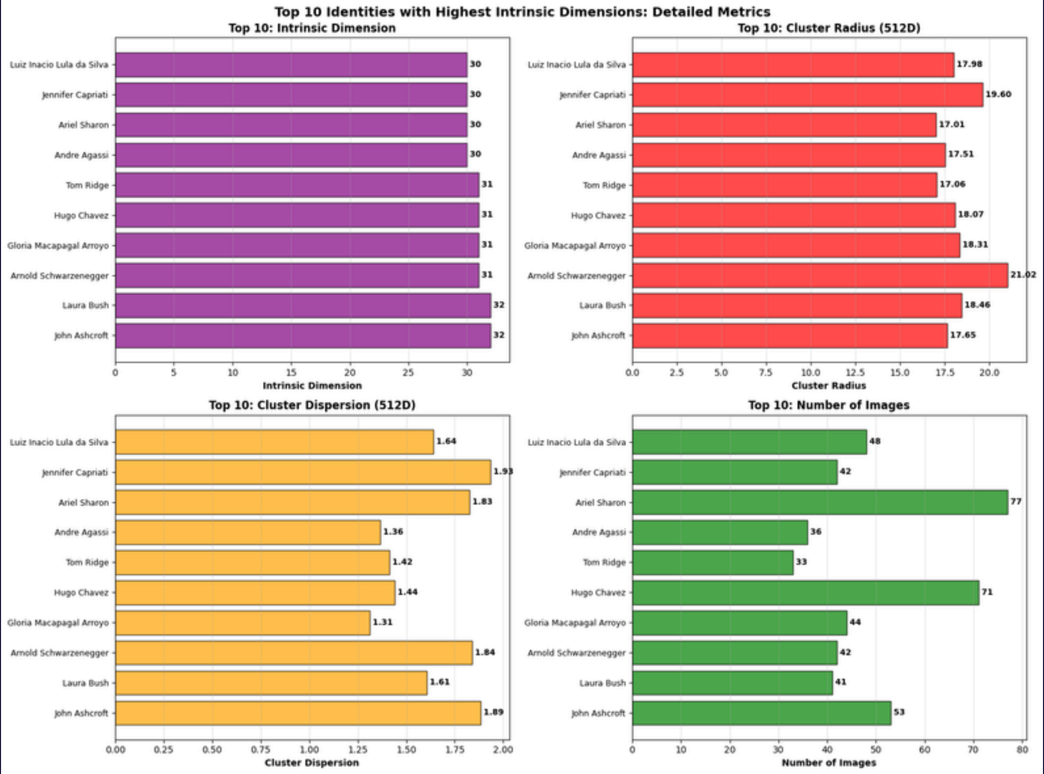
Identity	Intrinsic Dim	Radius	Dispersion	Num Images
Bill McBride	9	14.61	1.14	10
Ian Thorpe	9	17.82	1.56	10
Jacques Rogge	9	13.55	1.28	10
Jason Kidd	9	17.49	1.90	10
Javier Solana	9	14.66	1.08	10
Jean-David Levitte	9	15.53	1.41	10
Mohammad Khatami	9	18.26	1.77	10
Muhammad Ali	9	19.02	1.52	10
Paradorn Srichaphan	9	17.74	1.81	10
Paul Wolfowitz	9	15.84	1.42	10

Cluster Statistics Summary

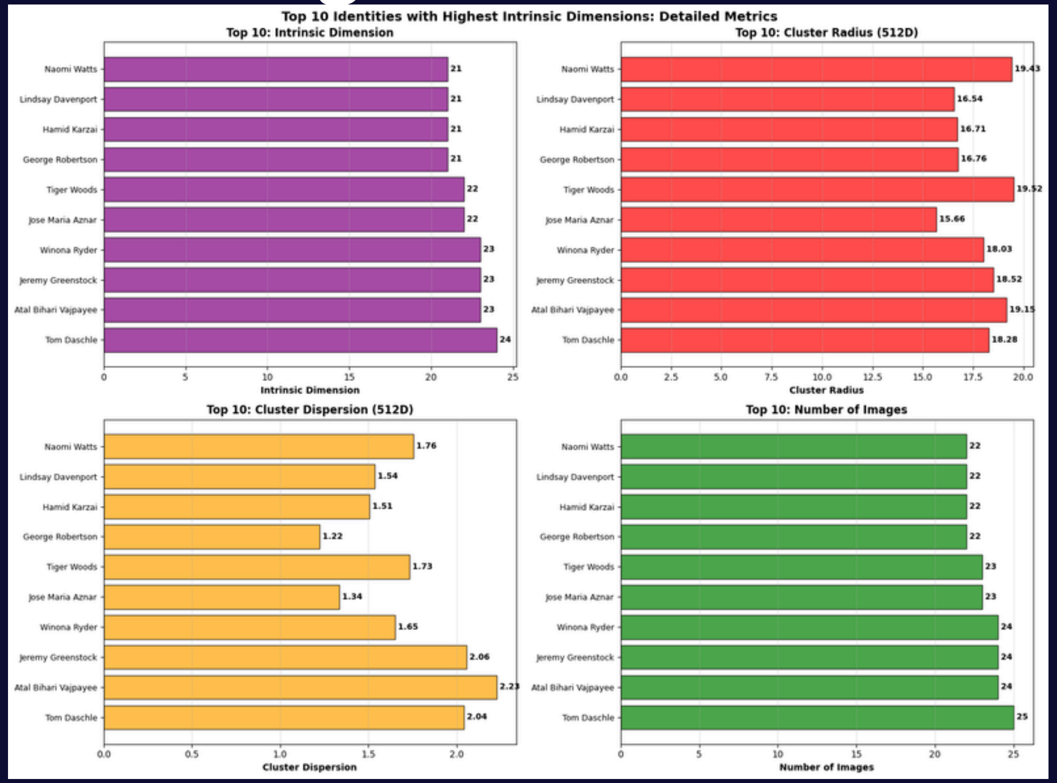
Metric	Max	Min	Mean
Radius (512D)	19.02	13.55	16.39
Dispersion	1.92	1.08	1.52
Num Images	10	10	10

Intrinsic Dimension Top10

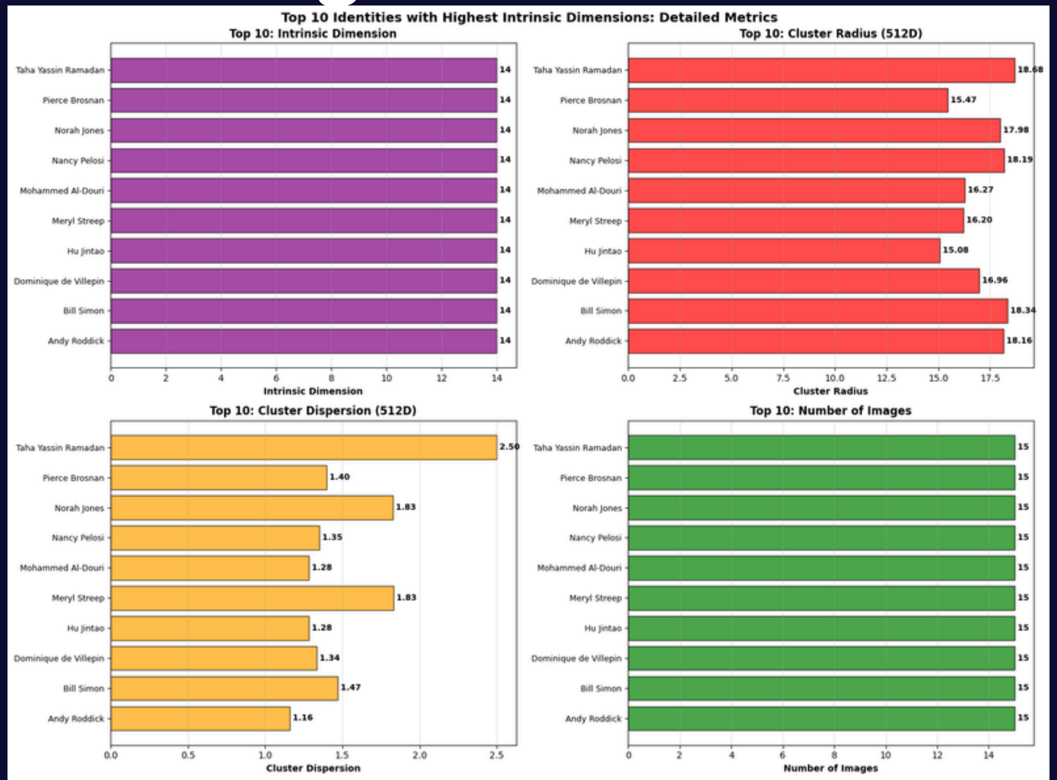
All imgs



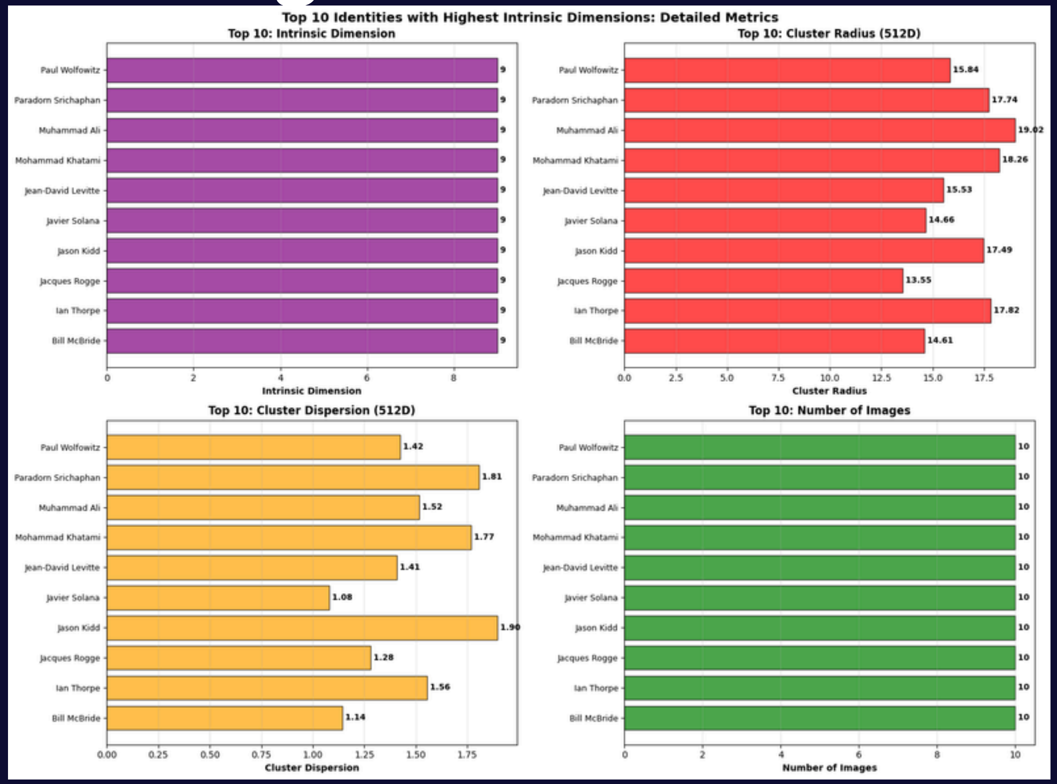
10-25 imgs



10-15 imgs

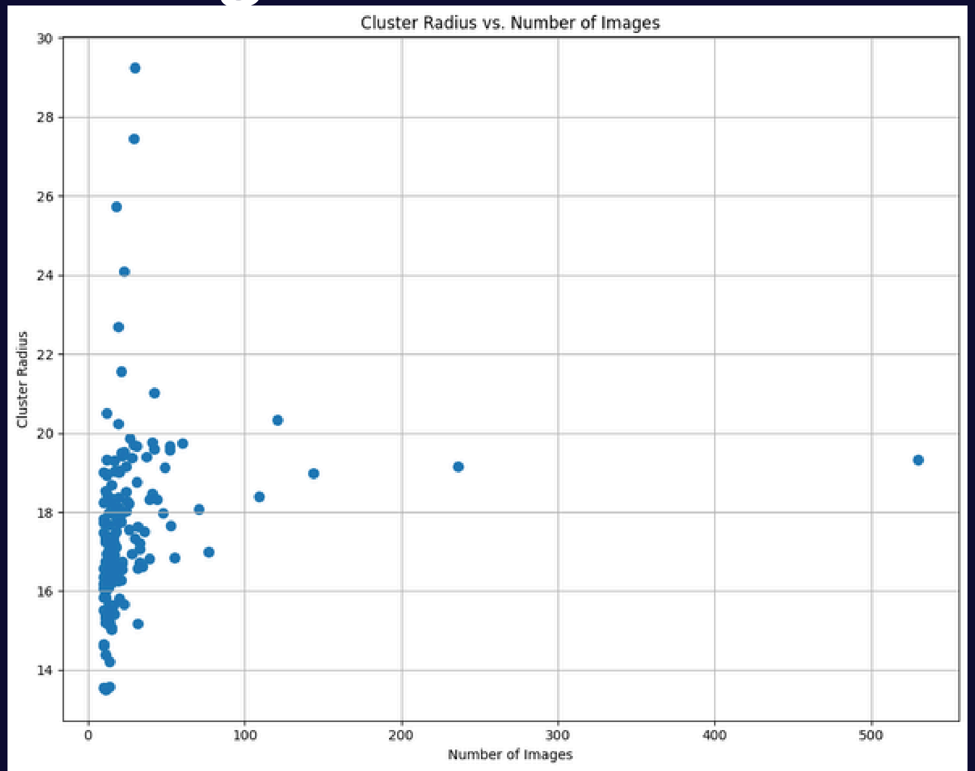


5-10 imgs

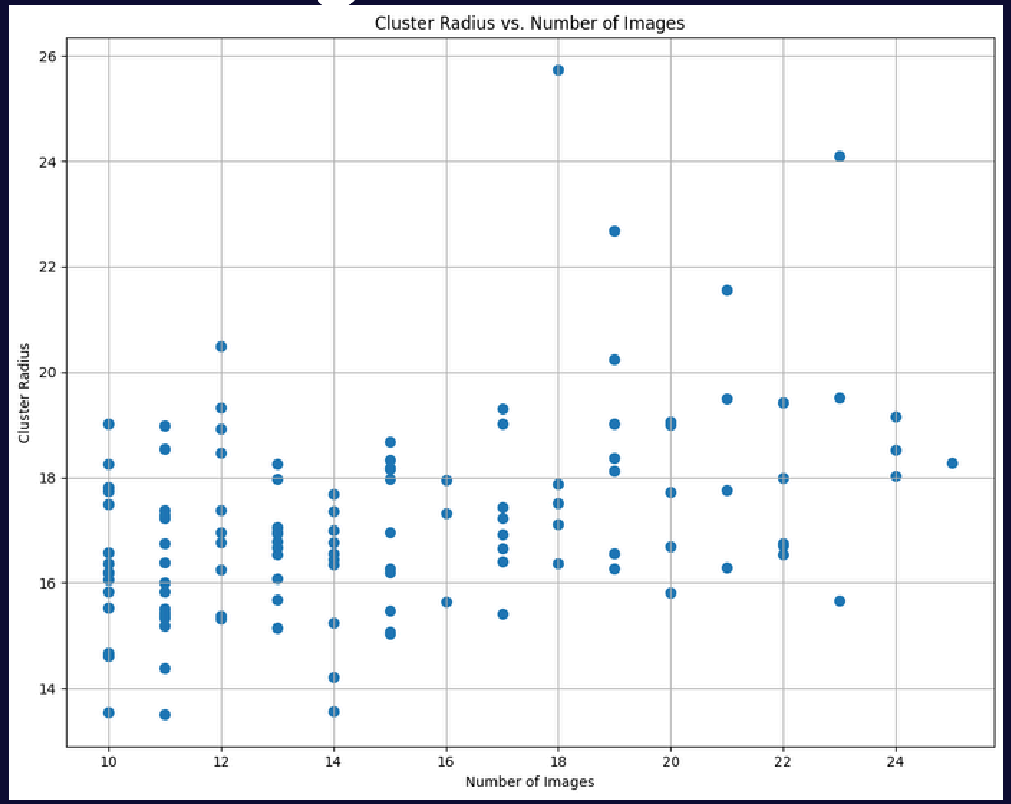


Scatter Plot: Radius and Number of Images

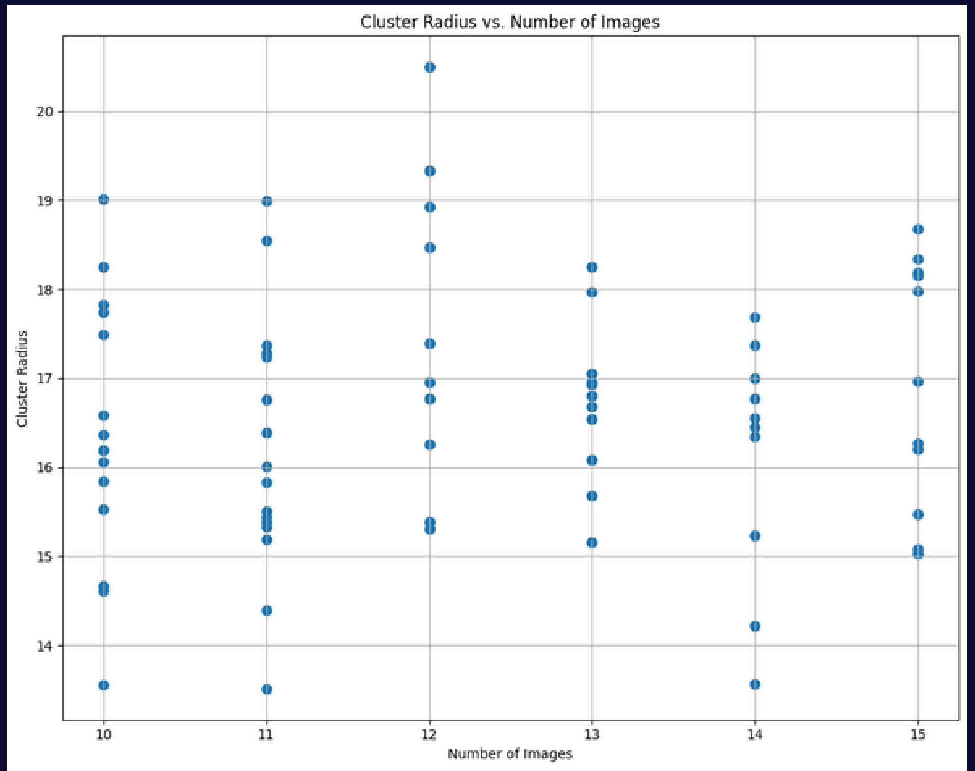
All imgs



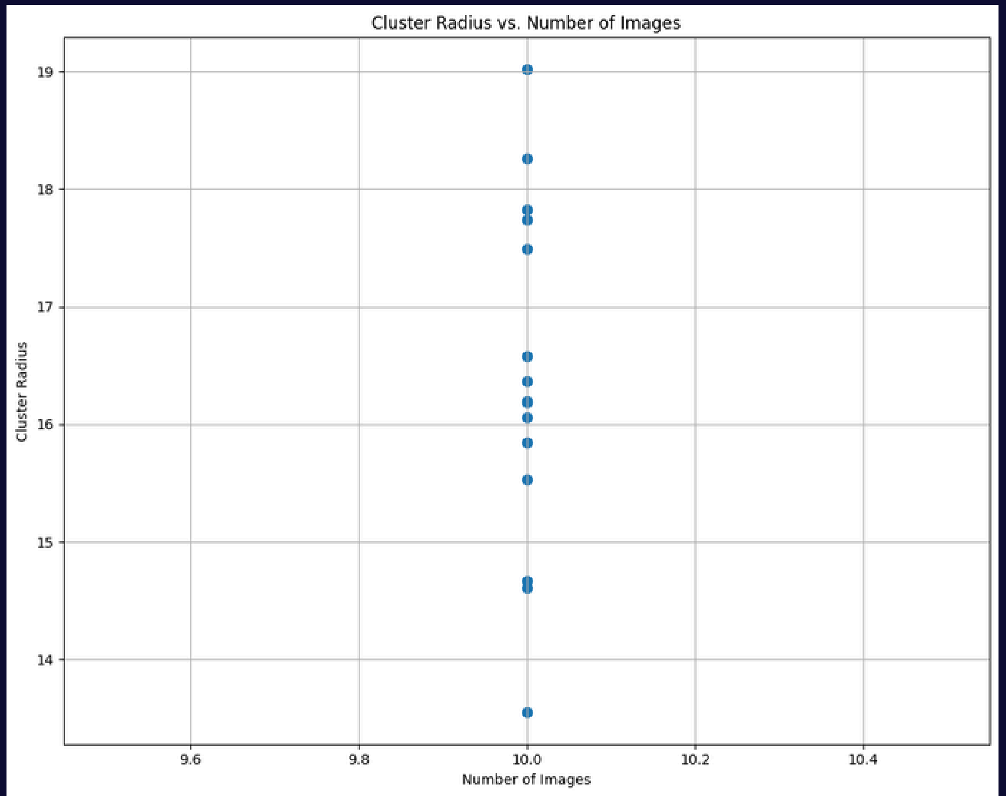
10-25 imgs



10-15 imgs



5-10 imgs



Future Work

- Made more efficient code to do all in 1 file, changing the parameters
- Repeat the same on the dataset FRGC
- VPN

Thank You