Controlling Memorability of Face Images

CNAILab Exploratory Summer

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Our Questions

1. What controls a facial image's ability to be remembered?

2. How can we manipulate to increase the memorability of a face image?

3. Can we quantifiably prove which traits are most important?

Related Works & Assurances

Image Memorability:

- Memorability has been shown to be an intrinsic feature of an image that is consistent across different observers.
- Can be measured and manipulated.

General Adversarial Networks (GANs):

- GANs have been shown to be a good tool for creating synthetic images
- Images can be modified through their latent vectors

StyleGAN

StyleGAN is a state-of-the-art model for generating and reconstructing real looking faces with high accuracy.

Creating the Dataset

10k US Adult Faces
Dataset

Flickr-Faces-HQ (FFHQ)
Dataset

Creating the Dataset cont.

Each newly generated image had its memorability predicted using computational memorability prediction models.

- SENet50, an assessor, was pre-trained with VGGFace2, a large scale face recognition dataset, and then fine-tuned on the 10k Face Database to correctly estimate face memorability scores.

The Hyperplane

Aim was to find a hyperplane to separate highly and lowly memorable face images.

- Logistic Regression used after organizing based on mean.
- Extended w-space was used for greater accuracy.
- Distance from the image's extended latent vector from this hyperplane is the memorability.

$$mem_i \propto d(\boldsymbol{w}^*, \boldsymbol{w}_i) = \boldsymbol{w}^{*^T} . \boldsymbol{w}_i$$

The Hyperplane cont.

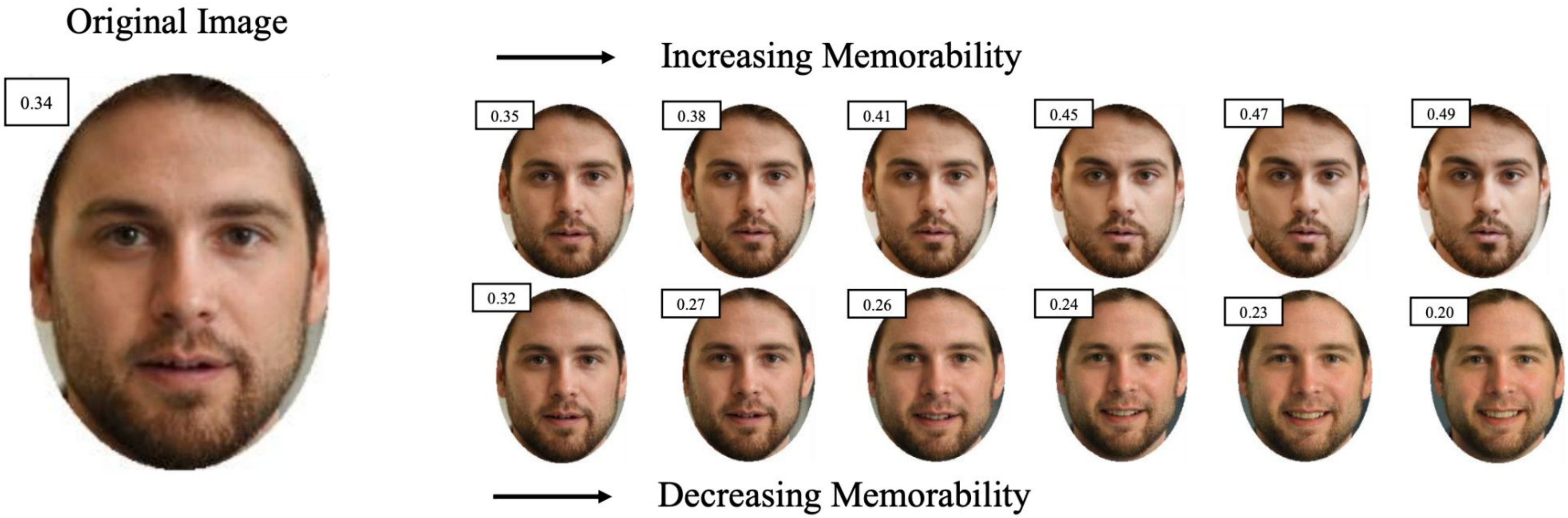
Memorability of any image can now be modified by changing the distance of its extended latent vector from the extended latent vector.

$$w_{edit} = w + \alpha w^*$$

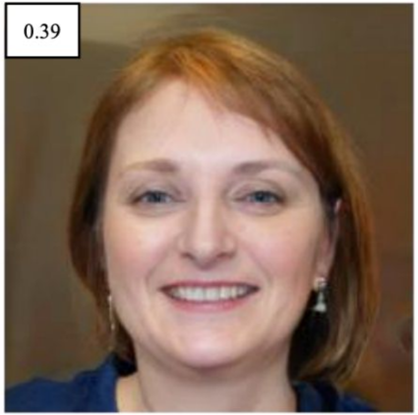
```
# new image vector = old image vector + magnitude * direction vector
x = np.ravel(lat1).copy() + 5 * w_sq
```

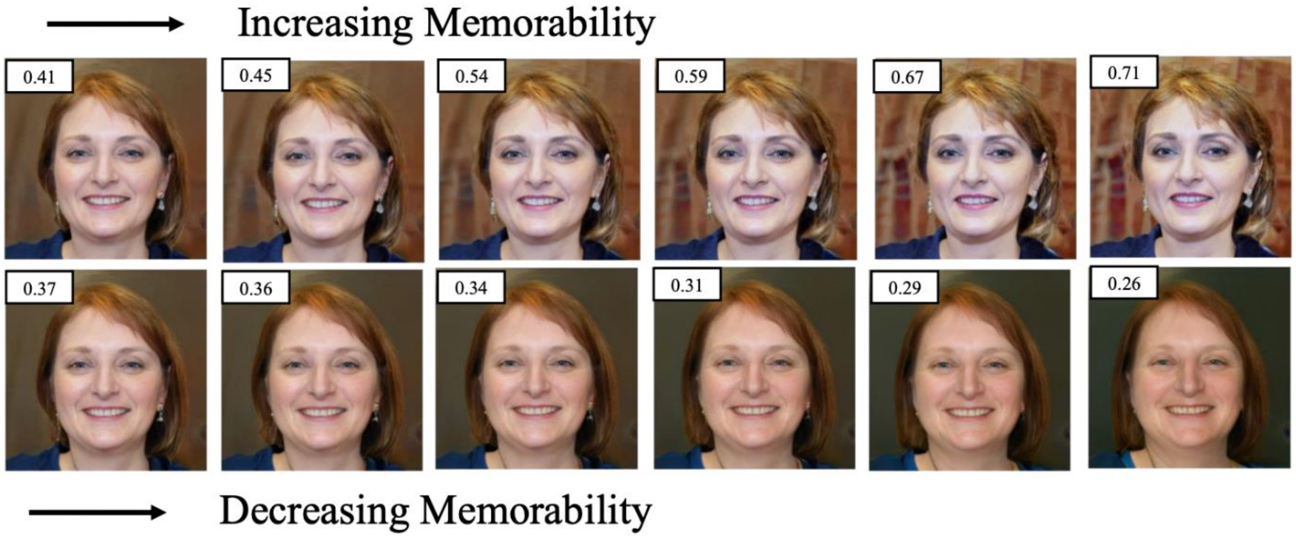
$$d(\boldsymbol{w}^*, \boldsymbol{w}_{edit}) = \boldsymbol{w}^{*^T} . \boldsymbol{w}_{edit} = \boldsymbol{w}^{*^T} . (\boldsymbol{w} + \alpha \boldsymbol{w}^*) = \boldsymbol{w}^{*^T} . \boldsymbol{w} + \alpha = d(\boldsymbol{w}^*, \boldsymbol{w}) + \alpha$$

Modifying Face Memorability

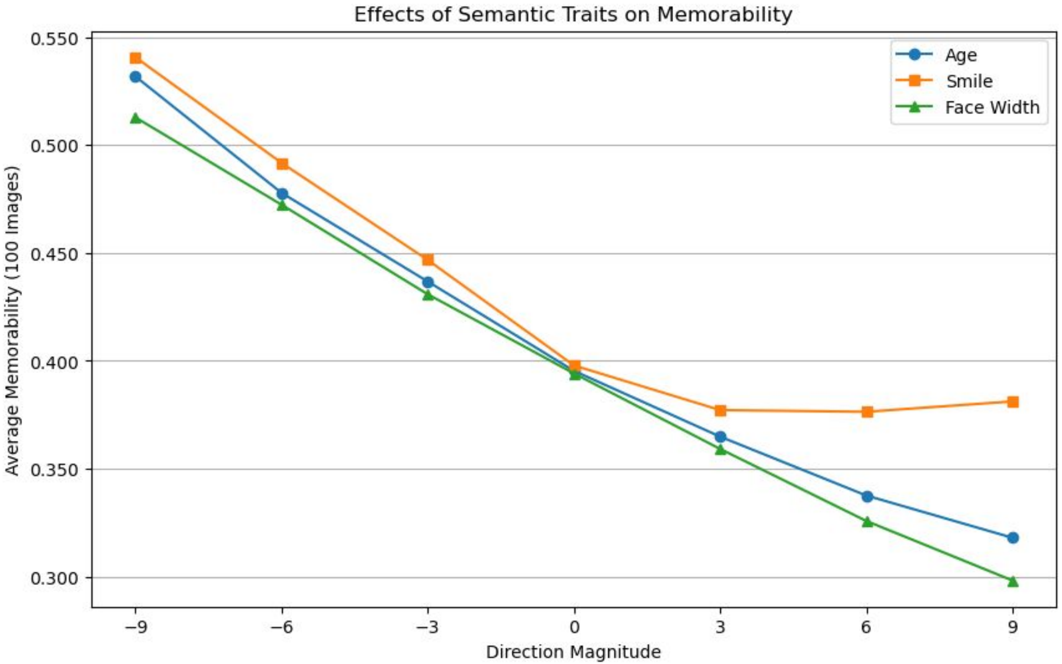


Modifying Face Memorability





Tests of Semantic Traits (100 img)



- Age decreases memorability
- Smile decreases memorability
- Face width decreases memorability

Conditional Modifications

A new vector direction can be created which still moves in the direction of a trait, but ignores another through projection.

- Projection can be done with vector directions to make N^T N a diagonal matrix where semantics are independent of each other.

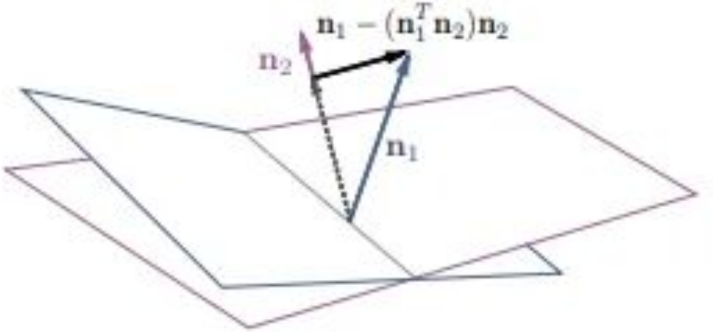


Fig. 2. Illustration of the **conditional manipulation via subspace projection**. The projection of $\mathbf{n}_1$ onto $\mathbf{n}_2$ is subtracted from $\mathbf{n}_1$, resulting in a new direction $\mathbf{n}_1 - (\mathbf{n}_1^T \mathbf{n}_2)\mathbf{n}_2$.

Conditional Manipulation

Original

0.3510

Memorability (+8)

0.7311

With Smile Condition

0.6039

Investigating Vector Structure

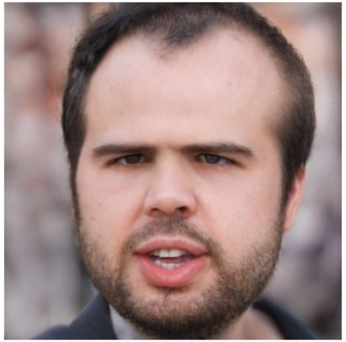
- Both image vectors and trait direction vectors share the same shape of (1, 18, 512)
- In all direction vectors, all 18 subvectors are equal
- What does each subvector represent?

Summary of 18 Subvectors

1/18 -> Face shape, orientation
2/18 -> Face orientation, body
3/18 -> Eye distance, hair
4/18 -> Hair length, smile
5/18 -> Smile, beard
6/18 -> Nose size, nose tilt
7/18 -> Gender, eye bags
8/18 -> Eye openness, colour
9/18 -> Beard, eyebrows
10/18 -> Eye colour
11/18 -> Colouring
12/18 -> Colouring
13/18 -> Colouring
14/18 -> Colouring/Texture
15/18 -> Colouring/Texture
16/18 -> Colouring/Texture
17/18 -> Colouring
18/18 -> Colouring/Texture

Vector 5/18

Smile, beard



Original Image
0.2961

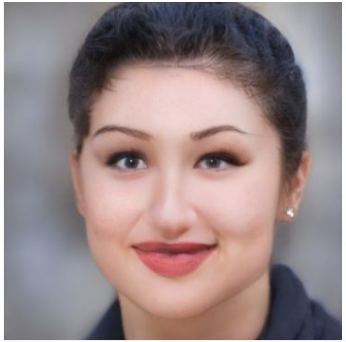
Dimension Dropped (0)
0.3446

Dimension Raised (15)
0.2986

Dimension Neg (-0.09)
0.5686

Vector 7/18

Gender, eye bags



Original Image
0.2961

Dimension Dropped (0)
0.2691

Dimension Raised (15)
0.2524

Dimension Neg (-0.10)
0.2972

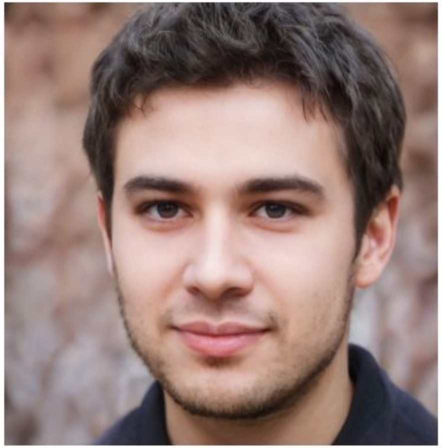
Memorability Subvectors

Which subvector/trait has the biggest impact in the memorability direction vector?

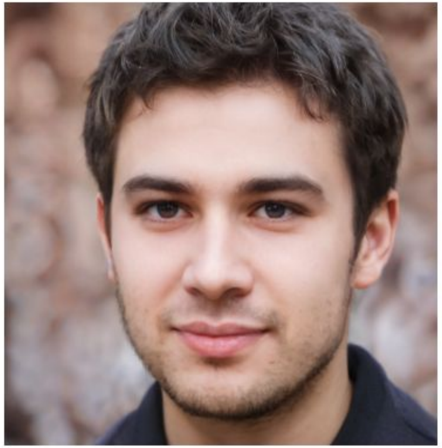
- Can’t look directly at value changes (they’re all equal) ✗
- What if we look at modifying with only 1 subvector at a time?

Subvector 1/18 - Memorability Direction

Original Image
0.2961



Mem Modified (12)
0.7565

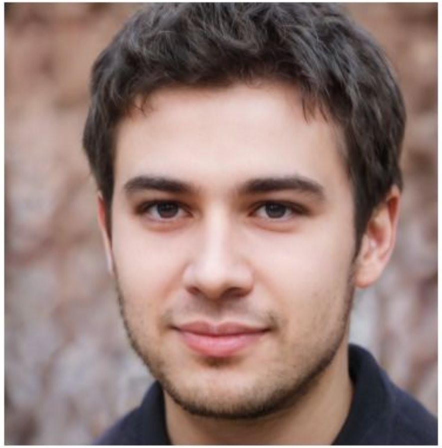


Subvector Dropped (0)
0.7472

Only Subvector
0.3070

Subvectors 4-7 - Memorability Direction

Original Image
0.2961



Mem Modified (12)
0.7565

Vectors Dropped (0)
0.5087

Only Vector
0.5163

Angle Differences

Which subvector/trait has the biggest impact in the memorability direction vector?

- Can’t look directly at value changes (they’re all equal) ✗
- Can’t look at subvectors one at a time (no image change) ✗
- What if we look at how the angle between the subvectors of the image and the subvectors of the direction vector change when increasing memorability?

Face 1 (Memorability)

-15*m
(0.082)

-7*m
(0.144)

Original Image
Mem: +0*m
(0.261)

+7*m
(0.444)

+15*m
(0.949)

Comparing Subvector-To-Subvector

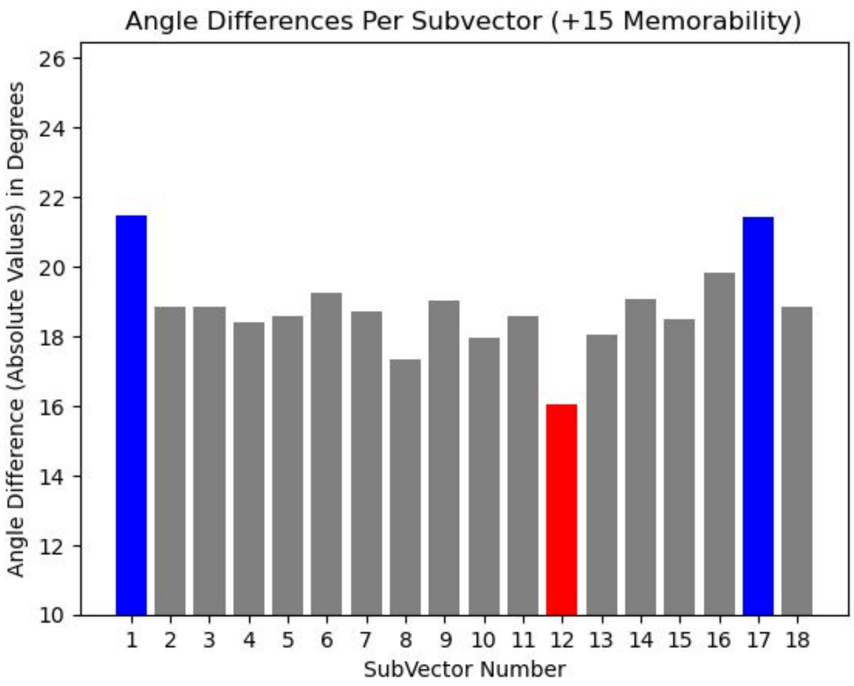
Original Image (+0) for Memorability:

Subvector 1: 88.497°
Subvector 2: 85.498°
Subvector 3: 87.569°
Subvector 4: 88.334°
Subvector 5: 89.054°
Subvector 6: 90.045°
Subvector 7: 85.398°
Subvector 8: 90.693°
Subvector 9: 87.659°

Subvector 10: 91.430°
Subvector 11: 89.124°
Subvector 12: 89.822°
Subvector 13: 89.883°
Subvector 14: 90.826°
Subvector 15: 89.847°
Subvector 16: 90.799°
Subvector 17: 88.543°
Subvector 18: 89.365°

Comparing Subvector-To-Subvector

Face 1 (+15) for Memorability:



Biggest Angle Changes:

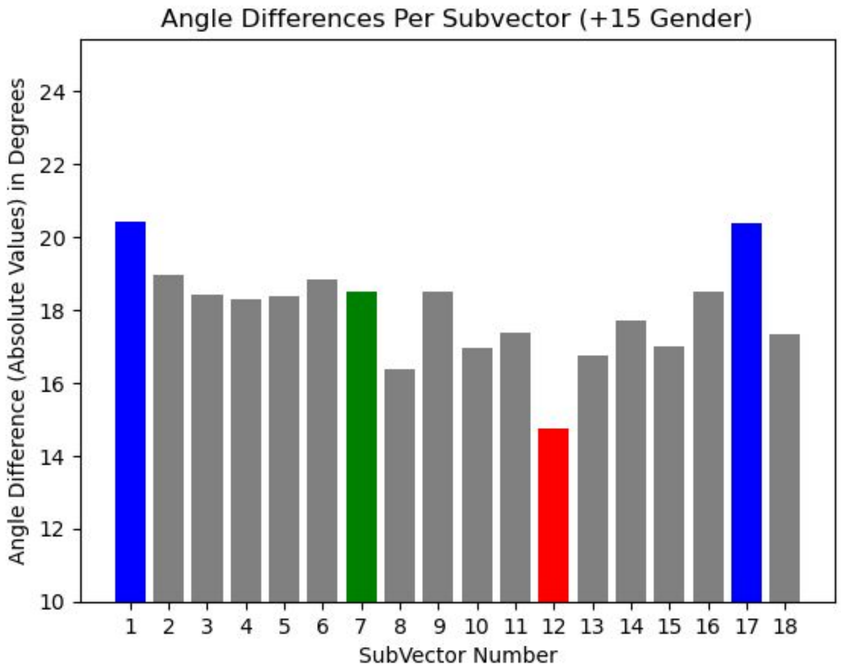
- Subvector 1: -21.98°
- Subvector 17: -21.96°

Smallest Angle Change:

- Subvector 12: -17.56°

Comparing Subvector-To-Subvector

Face 1 (+15) for Gender:



Biggest Angle Changes:

- Subvector 1: -22.72°
- Subvector 17: -21.96°

Smallest Angle Change:

- Subvector 12: -17.56°

Important Angle Change:

- Subvector 7: -20.69°

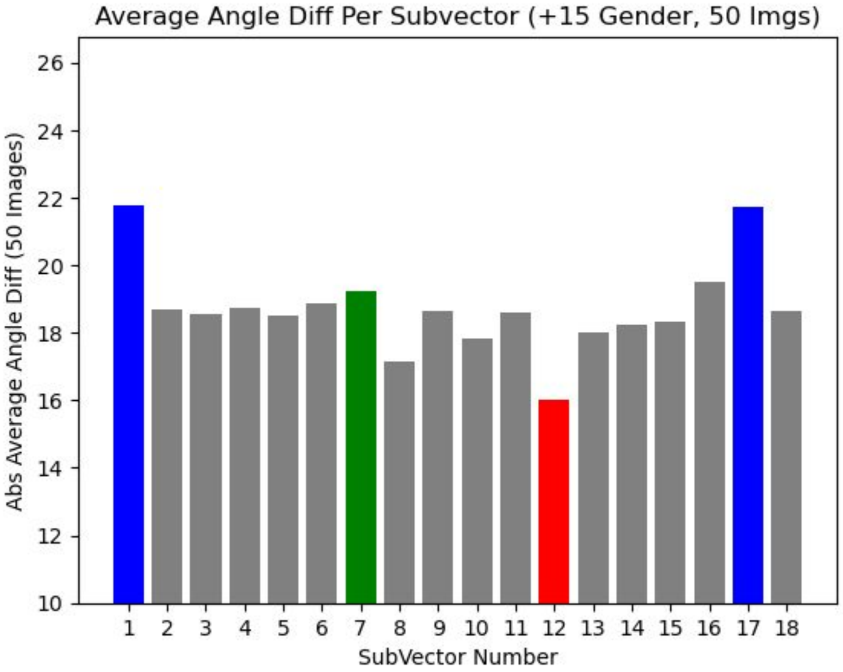
Investigating Our Method

Seeing if known subvector traits (smile = 5, gender = 7) are consistent with angle changes.

To do this the mean changes between 50 images were calculated.

Comparing Subvector-To-Subvector

Averages Angle Differences over 50 images for Gender (+15):



Biggest Angle Changes:

- Subvector 1: -21.75 ± 1.62°
- Subvector 17: -21.72 ± 1.08°

Smallest Angle Change:

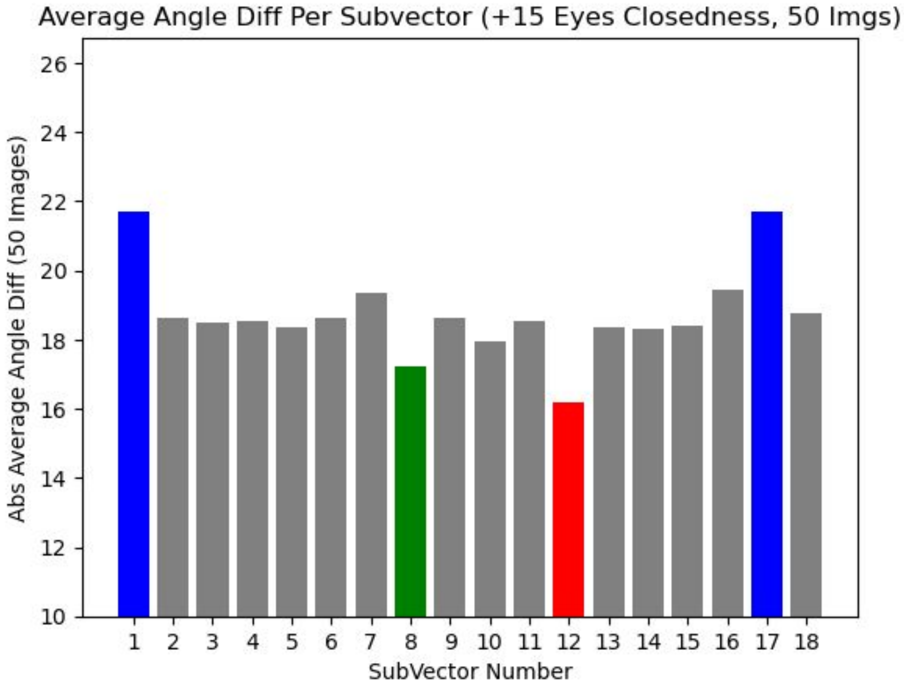
- Subvector 12: -16.03 ± 1.43°

Important Angle Change:

- Subvector 7: -19.24 ± 1.59°

Comparing Subvector-To-Subvector

Averages Angle Differences over 50 images for Eye Closedness (-15):



Biggest Angle Changes:

- Subvector 1: 21.72 ± 1.44°
- Subvector 17: 21.69 ± 1.44°

Smallest Angle Change:

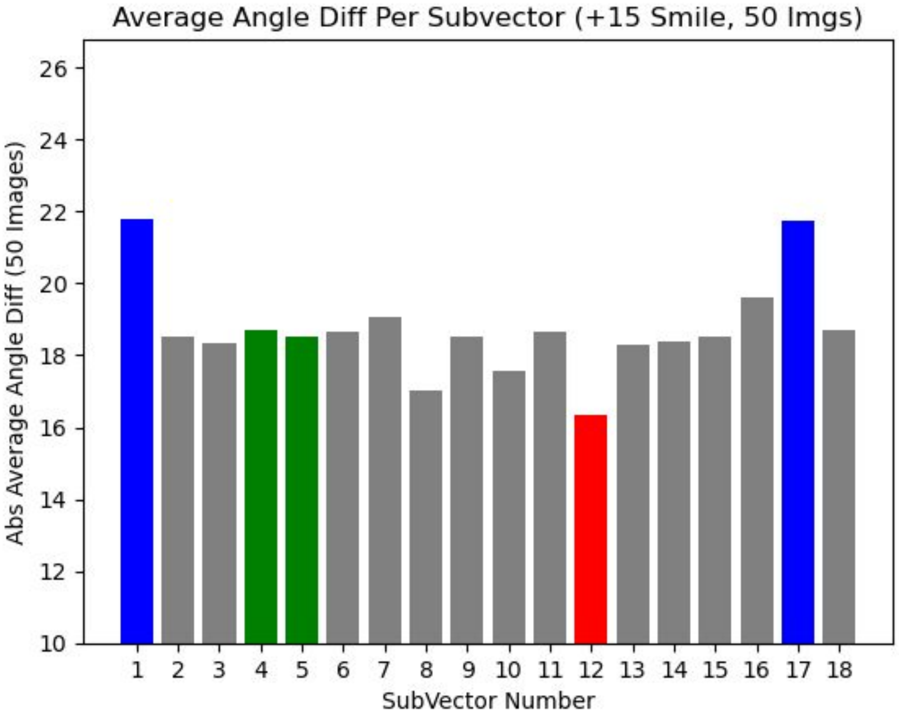
- Subvector 12: 16.19 ± 1.34°

Important Angle Change:

- Subvector 8: 17.23 ± 1.53°

Comparing Subvector-To-Subvector

Averages Angle Differences over 50 images for Smile (+15):



Biggest Angle Changes:

- Subvector 1: -21.78 ± 1.41°
- Subvector 17: -21.74 ± 1.41°

Smallest Angle Change:

- Subvector 12: -16.33 ± 1.32°

Important Angle Change:

- Subvector 4: -18.71 ± 1.51°
- Subvector 5: -18.51 ± 1.41°

Further Investigations ?

Once again, the same question remains unsolved.

Which subvector/trait has the biggest impact in the memorability direction vector?

- Can’t look directly at value changes (they’re all equal) ✗
- Can’t look at subvectors one at a time (no image change) ✗
- Can’t look at angle differences (no trait specific patterns) ✗
- What’s next?

Thank you for listening! :)