PSY 1406: Primate FaceNet Detection

Group Members: *Andrew Byun, Julia Casas, Ethan McFarlin, and Claire Suen*

Research Questions

- How does FaceNet perform on **non-human face recognition tasks?**

- What role do **gender** and **age** play in FaceNet’s detection capabilities?

- Can FaceNet help us gain insight into visual indicators of **evolutionary similarity?**

- Does FaceNet prove useful in **differentiating between species?**

Hypothesis

While FaceNet ***will*** be able to distinguish between **individual chimps** (by some statistically significant margin), it will **struggle** with more **advanced face recognition tasks** along the axes of gender, age, and interspecies identification.

To test this theory, we will pass input images from annotated datasets of **chimps**, **rhesus macaques,** and **Japanese Monkeys** into FaceNet and compute **statistical analysis** on the **euclidean distance scores**.

We will break this analysis into **4 questions** and carry out **independent** euclidean distance computations for each of them.

Question 1

Can FaceNet identify individual chimps?

Dataset and Wrangling

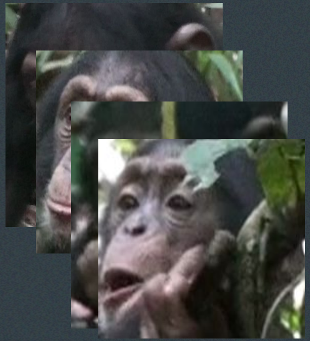
Name: Alexander Freytag and Erik Rodner and Marcel Simon and Alexander Loos and Hjalmar Kühl and Joachim Denzler: "Chimpanzee Faces in the Wild: Log-Euclidean CNNs for Predicting Identities and Attributes of Primates", German Conference on Pattern Recognition (GCPR), 2016.

Cleaned Data: 50 chimp images. Half of the images are of the same chimp named ‘Fredy’. The other half of the images depict different chimps.

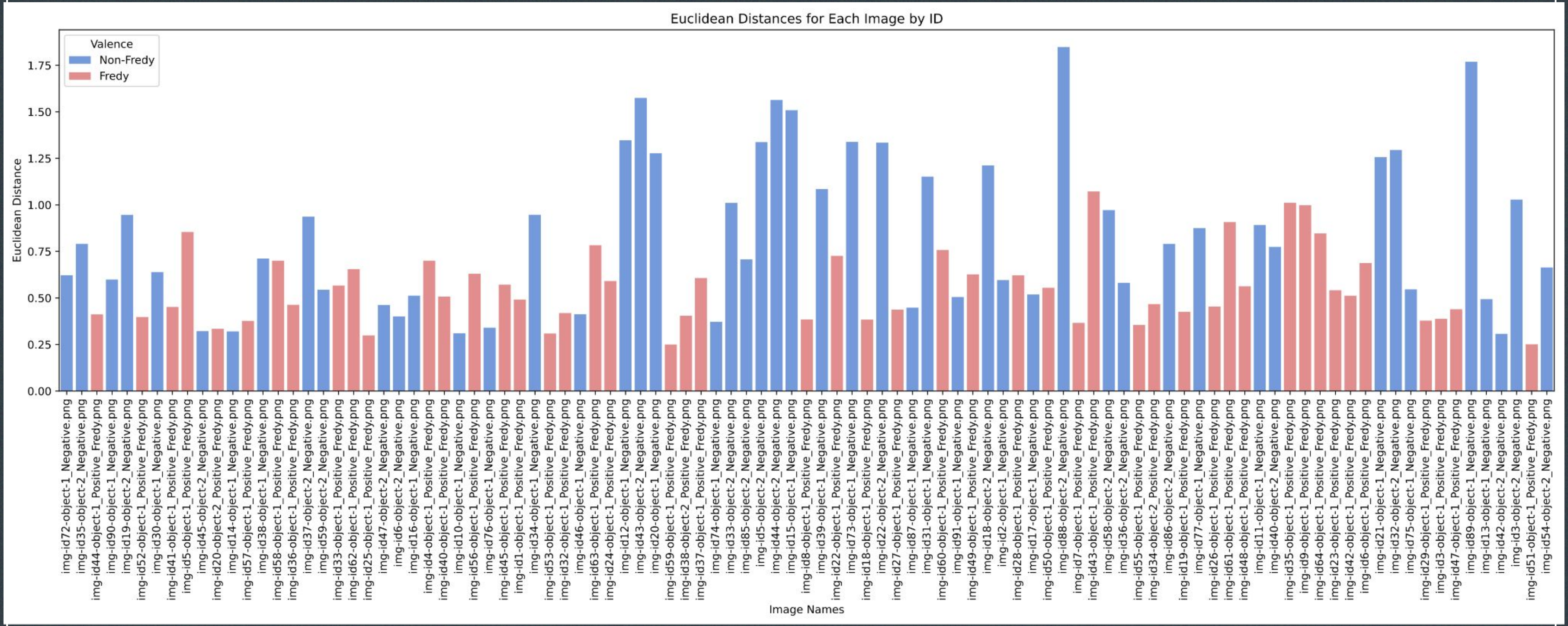
Negative/Positive/Anchor Images

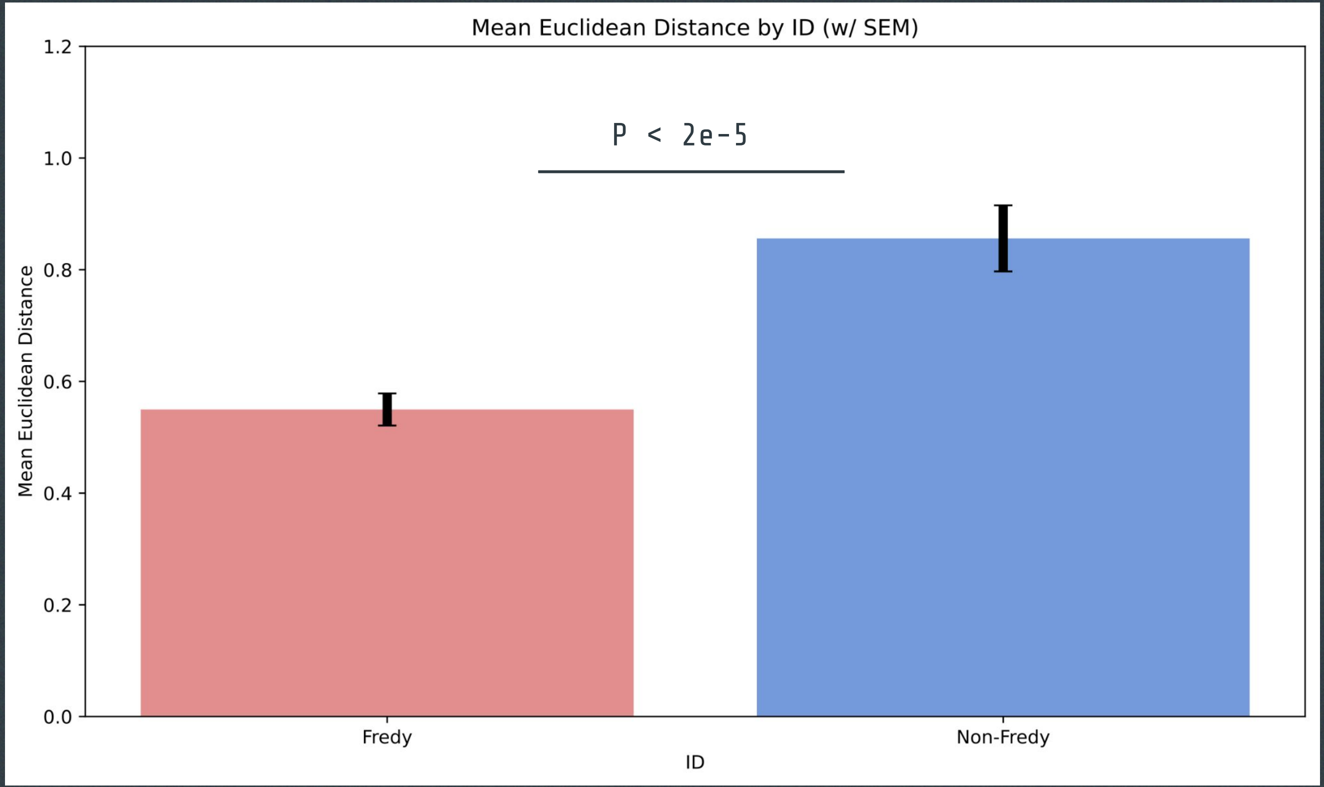
Positive: 49 Other Fredy Images

Negative: 50 Non-Fredy Chimp Images



Anchor: Fredy (Image ID #54)


Euclidean Distances for Each Image by ID
Valence
Non-Fredy
Fredy
Euclidean Distance
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
Image Names
img-id72-object-1_Negative.png
img-id35-object-2_Negative.png
img-id44-object-1_Positive_Fredy.png
img-id90-object-1_Negative.png
img-id19-object-2_Negative.png
img-id52-object-1_Positive_Fredy.png
img-id30-object-1_Negative.png
img-id41-object-1_Positive_Fredy.png
img-id5-object-1_Positive_Fredy.png
img-id45-object-2_Negative.png
img-id20-object-2_Positive_Fredy.png
img-id14-object-1_Negative.png
img-id57-object-1_Positive_Fredy.png
img-id38-object-1_Negative.png
img-id58-object-1_Positive_Fredy.png
img-id36-object-1_Positive_Fredy.png
img-id37-object-2_Negative.png
img-id59-object-2_Negative.png
img-id33-object-1_Positive_Fredy.png
img-id62-object-1_Positive_Fredy.png
img-id25-object-1_Positive_Fredy.png
img-id47-object-2_Negative.png
img-id6-object-2_Negative.png
img-id16-object-1_Negative.png
img-id4-object-1_Positive_Fredy.png
img-id40-object-1_Positive_Fredy.png
img-id10-object-1_Negative.png
img-id56-object-1_Positive_Fredy.png
img-id76-object-1_Negative.png
img-id45-object-1_Positive_Fredy.png
img-id1-object-1_Positive_Fredy.png
img-id34-object-1_Negative.png
img-id53-object-1_Positive_Fredy.png
img-id32-object-1_Positive_Fredy.png
img-id46-object-1_Negative.png
img-id63-object-1_Positive_Fredy.png
img-id24-object-1_Positive_Fredy.png
img-id12-object-1_Negative.png
img-id43-object-2_Negative.png
img-id20-object-1_Negative.png
img-id59-object-1_Positive_Fredy.png
img-id38-object-2_Positive_Fredy.png
img-id37-object-1_Positive_Fredy.png
img-id74-object-1_Negative.png
img-id33-object-2_Negative.png
img-id85-object-2_Negative.png
img-id5-object-2_Negative.png
img-id44-object-2_Negative.png
img-id15-object-1_Negative.png
img-id8-object-1_Positive_Fredy.png
img-id39-object-1_Negative.png
img-id22-object-1_Positive_Fredy.png
img-id73-object-1_Negative.png
img-id18-object-1_Positive_Fredy.png
img-id22-object-2_Negative.png
img-id27-object-1_Positive_Fredy.png
img-id87-object-1_Negative.png
img-id31-object-1_Negative.png
img-id60-object-1_Positive_Fredy.png
img-id91-object-1_Negative.png
img-id49-object-1_Positive_Fredy.png
img-id18-object-2_Negative.png
img-id2-object-1_Negative.png
img-id28-object-1_Positive_Fredy.png
img-id17-object-1_Negative.png
img-id50-object-1_Positive_Fredy.png
img-id88-object-2_Negative.png
img-id7-object-1_Positive_Fredy.png
img-id43-object-1_Positive_Fredy.png
img-id58-object-2_Negative.png
img-id36-object-2_Negative.png
img-id55-object-1_Positive_Fredy.png
img-id34-object-2_Positive_Fredy.png
img-id86-object-2_Negative.png
img-id19-object-1_Positive_Fredy.png
img-id77-object-1_Negative.png
img-id26-object-1_Positive_Fredy.png
img-id61-object-1_Positive_Fredy.png
img-id48-object-1_Positive_Fredy.png
img-id11-object-1_Negative.png
img-id40-object-2_Negative.png
img-id35-object-1_Positive_Fredy.png
img-id9-object-1_Positive_Fredy.png
img-id64-object-1_Positive_Fredy.png
img-id23-object-1_Positive_Fredy.png
img-id42-object-1_Positive_Fredy.png
img-id6-object-1_Positive_Fredy.png
img-id21-object-1_Negative.png
img-id32-object-2_Negative.png
img-id75-object-1_Negative.png
img-id29-object-1_Positive_Fredy.png
img-id3-object-1_Positive_Fredy.png
img-id47-object-1_Positive_Fredy.png
img-id89-object-1_Negative.png
img-id13-object-1_Negative.png
img-id42-object-2_Negative.png
img-id3-object-2_Negative.png
img-id51-object-1_Positive_Fredy.png
img-id54-object-2_Negative.png


Mean Euclidean Distance by ID (w/ SEM)
P < 2e-5
Mean Euclidean Distance
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Fredy
Non-Fredy
ID

Question 2

Can FaceNet discriminate between gender within species?

Description of Dataset (Question 2-4)

Name: PrimFace (Face database of non-human primates)
https://visiome.neuroinf.jp/primface/

Primate Types: Japanese Monkey, Rhesus Macaque, Chimpanzee with metadata on gender and age

30 Images of n=3 for each of the primate types were used

Negative/Positive/Anchor Images

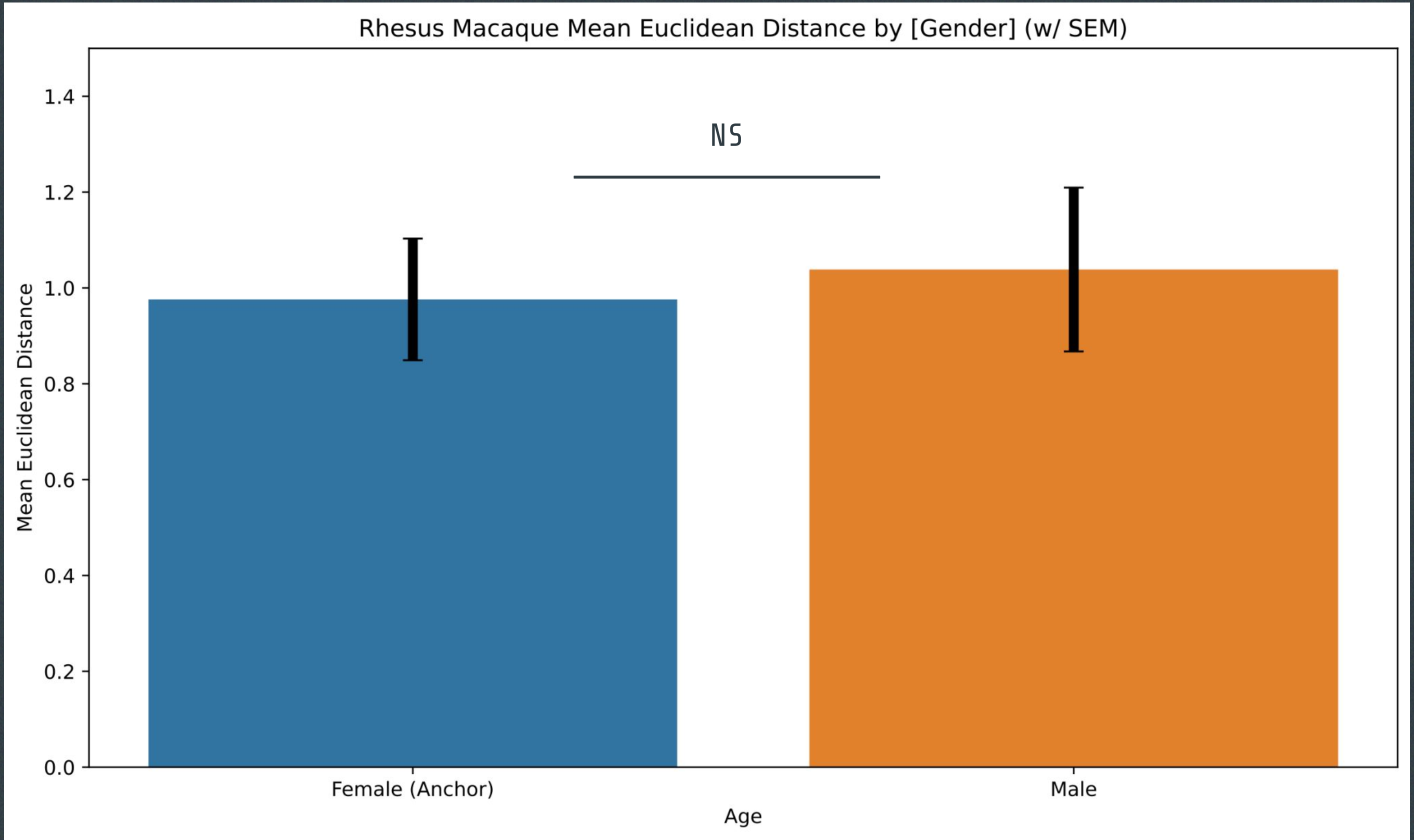
Anchor:
Rhesus Macaque
(Female/Age:5)

Positive:
Rhesus Macaque
(Female/Age:5)
Different angled images

Negative:
Rhesus Macaque
(Female/Age:20)

Rhesus Macaque
(Male/Age:5)

This design allows us to investigate discriminative capacity of FaceNet on Rhesus Macaque gender, but also Age (Question 3)


Rhesus Macaque Mean Euclidean Distance by [Gender] (w/ SEM)
Mean Euclidean Distance
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
NS
Female (Anchor)
Male
Age

Can Facenet recognize males more accurately than females?

```
        Welch Two Sample t-test

data:  Distance by Gender
t = 0.90026, df = 93.878, p-value = 0.3703
alternative hypothesis: true difference in means between group FE and group MA is not equal to 0
95 percent confidence interval:
 -0.08671091  0.23056604
sample estimates:
mean in group FE mean in group MA
        1.262022         1.190094
```

Can Facenet recognize males more accurately than females, controlling for age?

```
Call:
lm(formula = Distance ~ Gender + Age, data = data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.90429 -0.25136  0.02597  0.31291  0.69682 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.207785   0.104450  11.563   <2e-16 ***
GenderMA    -0.048396   0.090840  -0.533    0.595    
Age          0.001856   0.003399   0.546    0.586    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4053 on 94 degrees of freedom
Multiple R-squared:  0.01061,	Adjusted R-squared:  -0.01044 
F-statistic: 0.5042 on 2 and 94 DF,  p-value: 0.6056
```

Analysis of Variance Table

Response: Distance

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Gender	1	0.1167	0.116694	0.7102	0.4015
Age	1	0.0490	0.048993	0.2982	0.5863
Residuals	94	15.4446	0.164304		

Can Facenet recognize males more accurately than females, controlling for age groups?

```
Call:
lm(formula = Distance ~ Gender + Age_Group, data = data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.90936 -0.24341  0.00943  0.28484  0.74404 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)        1.24963    0.06647  18.801   <2e-16 ***
GenderMA          -0.04345    0.09254  -0.470   0.6398    
Age_GroupElderly   0.02187    0.14311   0.153   0.8789    
Age_GroupInfant    0.05714    0.10274   0.556   0.5795    
Age_GroupJuvenile -0.28612    0.15743  -1.817   0.0724 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4008 on 92 degrees of freedom
Multiple R-squared:  0.05339,	Adjusted R-squared:  0.01223 
F-statistic: 1.297 on 4 and 92 DF,  p-value: 0.277
```

```
Analysis of Variance Table

Response: Distance
          Df  Sum Sq Mean Sq F value Pr(>F)
Gender     1  0.1167 0.11669  0.7265 0.3962
Age_Group  3  0.7167 0.23890  1.4874 0.2232
Residuals 92 14.7768 0.16062
```

Exploratory Analysis: Can we predict euclidean distance based on age group while controlling for gender?

```
Call:
lm(formula = Distance ~ Age_Group + Gender, data = data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.90936 -0.24341  0.00943  0.28484  0.74404 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)         1.24963    0.06647  18.801   <2e-16 ***
Age_GroupElderly    0.02187    0.14311   0.153   0.8789    
Age_GroupInfant     0.05714    0.10274   0.556   0.5795    
Age_GroupJuvenile -0.28612    0.15743  -1.817   0.0724 .  
GenderMA          -0.04345    0.09254  -0.470   0.6398    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4008 on 92 degrees of freedom
Multiple R-squared:  0.05339,	Adjusted R-squared:  0.01223 
F-statistic: 1.297 on 4 and 92 DF,  p-value: 0.277
```

Analysis of Variance Table

Response: Distance

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Age_Group	3	0.7980	0.265994	1.6561	0.1820
Gender	1	0.0354	0.035417	0.2205	0.6398
Residuals	92	14.7768	0.160618		

Exploratory Analysis: Can we predict euclidean distance based on age group while controlling for gender?

```
Call:
lm(formula = Distance ~ Age + Gender, data = data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.90429 -0.25136  0.02597  0.31291  0.69682 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.207785   0.104450  11.563   <2e-16 ***
Age          0.001856   0.003399   0.546    0.586    
GenderMA    -0.048396   0.090840  -0.533    0.595    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4053 on 94 degrees of freedom
Multiple R-squared:  0.01061,	Adjusted R-squared:  -0.01044 
F-statistic: 0.5042 on 2 and 94 DF,  p-value: 0.6056
```

```
Analysis of Variance Table

Response: Distance
          Df  Sum Sq  Mean Sq F value Pr(>F)
Age        1  0.1191 0.119053  0.7246 0.3968
Gender     1  0.0466 0.046634  0.2838 0.5955
Residuals 94 15.4446 0.164304
```

Discussion (Broad)

- Facenet's sensitivity to Chimp faces:
  - Training data bias
  - Feature emphasis discrepancy: Facenet is trained to emphasize and distinguish among human faces (eye spacing, facial symmetry, etc) which might not be as pronounced in Chimps
  - Facial structure and variability differences: can lead to misinterpretation or overlooked by algorithm
- Gender differences in chimp:
  - gender differences are not pronounced enough to be detected
- Age as a confounding factor:
- Sample Size and Study design:
  - Can replicate using different chimps as "anchor"
  - if effect size is small, larger sample sizes are necessary to detect significant differences

Discussion (Algorithm)

- **Triplet Loss Function**: used to ensure that an image of a specific person's face is closer to all other images of the same person than to any image of any other person in the dataset
  - Chimps: struggle with subtle differences or misaligned of features

- **CNN**: used for feature extraction, tuned to human facial features (eyes, noses, mouths) in specific configurations and proportions

- **Embedding layer**: Used to compare faces and determine similarity

Question 3

Can FaceNet discriminate **age** within species?

Negative/Positive/Anchor Images

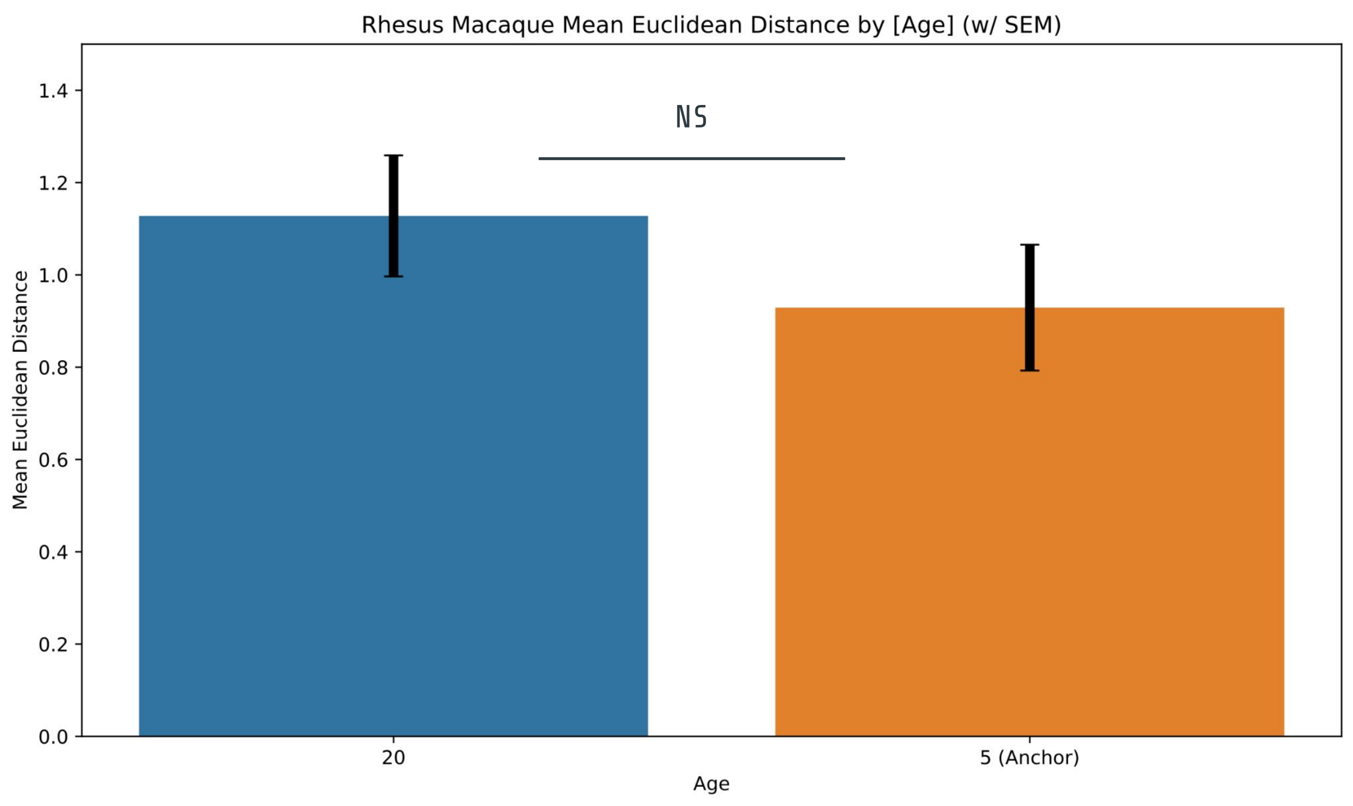
Anchor:
Rhesus Macaque
(Female/Age:5)

Positive:
Rhesus Macaque
(Female/Age:5)
Different angled images

Negative:
Rhesus Macaque
(Female/Age:20)

Rhesus Macaque
(Male/Age:5)

This design allows us to investigate discriminative capacity of FaceNet on Rhesus Macaque gender, but also Age (Question 3)


Rhesus Macaque Mean Euclidean Distance by [Age] (w/ SEM)
NS
Mean Euclidean Distance
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
20
5 (Anchor)
Age

Question 4

Can FaceNet discriminate across species?
(Chimps vs Rhesus vs Jap. Monkey)

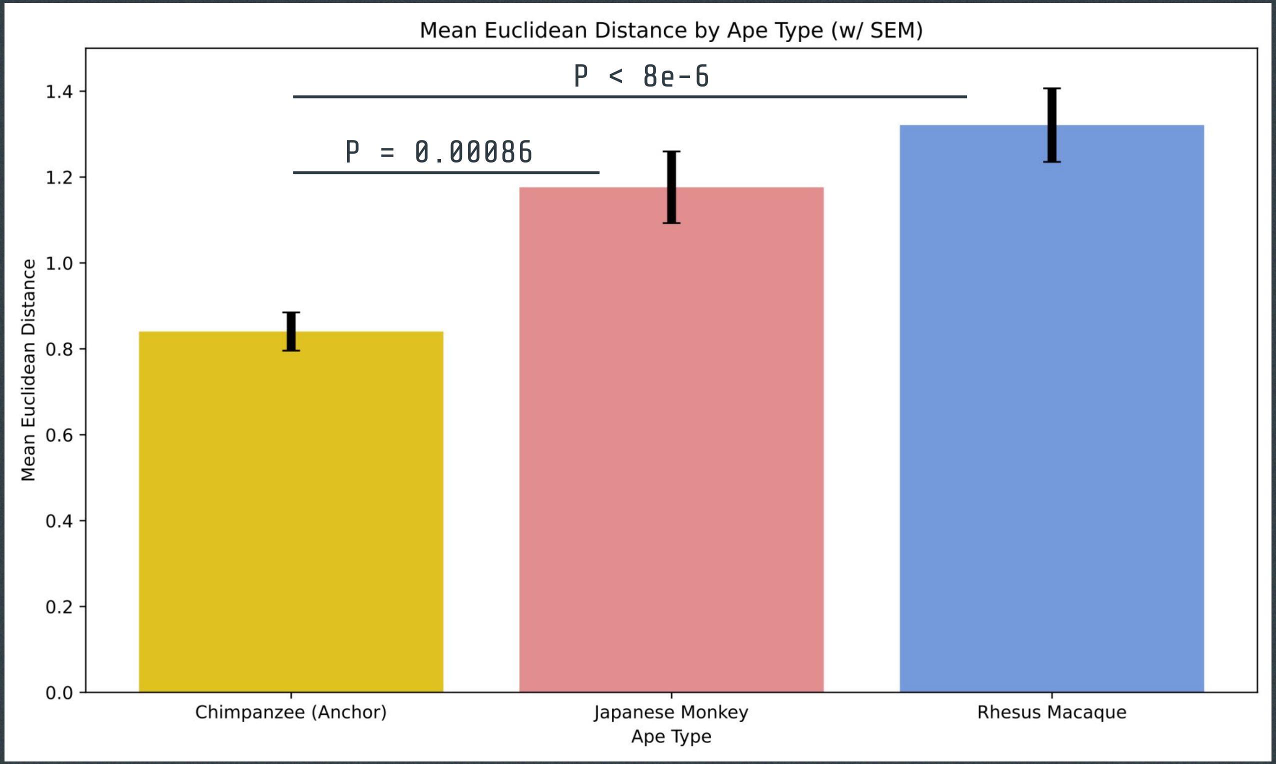
Negative/Positive/Anchor Images

Anchor:
Chimpanzee
(Female/Age:34)

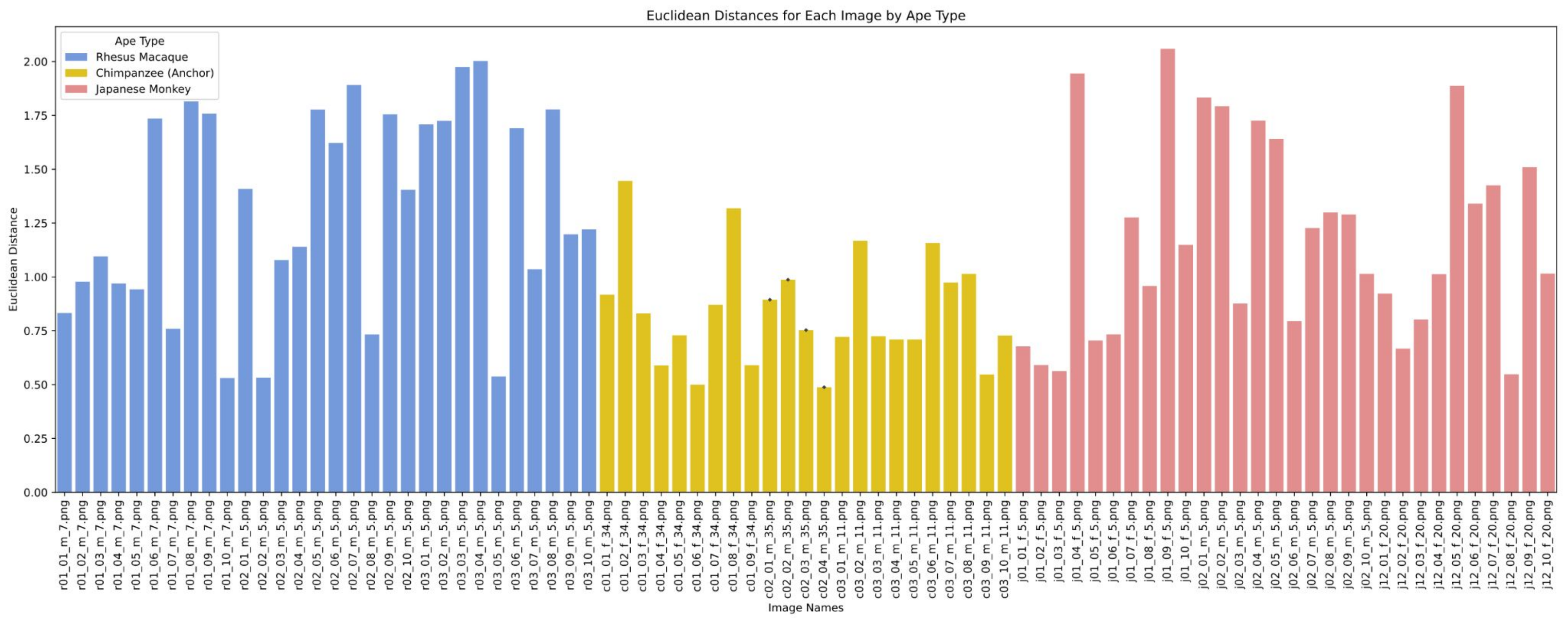
Positive:
30 Images of 3
Chimpanzees

Negative:
30 Images of 3 Rhesus Macaques,
30 Images of Japanese Monkeys

Can FaceNet distinguish Ape Types?



Can FaceNet distinguish Ape Types?



Conclusion

Q&A

thank you for your time and attention!