



Generative Aging of Photographs for Kinship Verification

Zoe Ghiron (zghiron@stanford.edu)

Yash Chandramouli (yashc3@stanford.edu)

Aeronautics/Astronautics Department, Stanford University

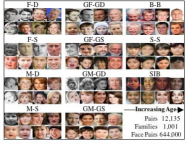


Motivation

- Kinship verification has applications to paternity testing, human trafficking, and genetics.
- Inputs are a pair of face images, output is whether they are blood relatives
- Current methods using photographs have seemed to stagnate at around 70% accuracy
- Through pre-processing inputs with a generative aging algorithm we were able to increase performance in a model-agnostic way

Data and Features

- Data came from Families in the Wild (FIW)^[4]
- 50,000 color image pairs of 11 different classes of family relationships (Father-Daughter, Grandmother-Grandson, etc.)



	Training	Dev	Test
	153 families	5 families	5 families
	46,735 triplets	3,276 pairs	1,558 pairs

- For CNN training the outputted "features" were encodings of the images.
- The generative networks were learning features that corresponded to the facial manifold so they could properly age the faces.

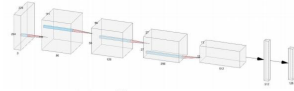
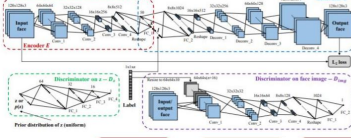
Modeling

CNN^[1]

1. Triplet Loss: $L(A, P, N) = \max(\|A - P\|_2^2 - \|A - N\|_2^2 + \alpha, 0)$ where α was empirically chosen to be 0.4
2. $D = \|encoding_1 - encoding_2\|_2^2$, where $D > \epsilon$ means the two inputs are relatives, ϵ chosen from dev set

CAAE^[2]

Attempts to age faces by propagating certain features across facial manifold.



IPCGAN^[3]

Uses an age estimator and an identity-preserving condition to decrease unnecessary smoothing in age-progressed faces.

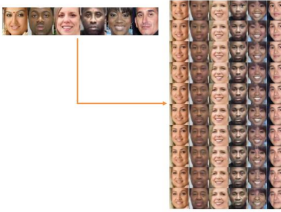


Discussion

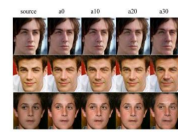
- As hypothesized, the best option for accuracy was to age the images to a younger age.
- The best CAEE age was category 2 not category 1 likely because category 1 had too many false positives (encodings were too similar overall)
- Aging forward using IPCGAN yielded the highest precision, likely because the preserved features made encodings inherently more different
- Overall saw up to a 3% boost in accuracy. This is raised to a 5% boost in accuracy by adjusting hyper-params.

Results

CAAE- 20 epochs



IPCGAN- Pretrained



GAN	Age category	Accuracy	Precision	Recall
CAAE	NA - no pre-processing	57.7	60.1	48.9
	Category 1	56.7	56.5	63.7
	Category 2	60.4	60.7	62.1
	Category 3	58.8	59.6	58
	Category 4	60.2	61.6	57.1
	Category 5	59	60.9	53.2
	Category 6	58.8	60.6	53.6
	Category 7	58.7	61.6	49.1
	Category 8	56.3	58.6	46.9
	Category 9	56.5	58.8	47.3
	Category 10	55.3	57.7	44.1
IPC	Category 1	57.1	59.3	48.9
	Category 2	57.1	59.8	46.9
	Category 3	57.1	60.9	43
	Category 4	56.7	60.7	41.4
	Category 5	57.6	63.1	39.4

Table 5: Results with GAN's preprocessing

References

- [1] Weiyang Liu, Yandong Wen, Zhiding Yu, Ming Li, Bhiksha Raj, and Le Song. Sphreface: Deep hypersphere embedding for face recognition. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017.
- [2] Zhifei Zhang, Yang Song, and Hairong Qi. Age progression/regression by conditional adversarial autoencoder. In IEEE Conference on Computer Vision and Pattern Recognition, University of Tennessee, Knoxville, 2017.
- [3] Zongwei Wang, Xu Tang, Weixin Luo, and Shenghua Gao. Face aging with identity-preserved conditional generative adversarial networks. In IEEE Conference on Computer Vision and Pattern Recognition, 2017.
- [4] Joseph P Robinson, Ming Shao, Yue Wu, and Yun Fu. Families in the wild(fiw): Large-scale kinship image database and benchmarks. In IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 40, No.11. IEEE, November 2018.

Future Work

- See if can apply to SphereFace for state-of-the-art performance
- Use an age/gender estimator to generate more interesting aging policies (such as aging to the average age, or the age of the younger photo, etc.)