Computational insights into human expertise for (un)familiar face recognition

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Accepted manuscript pre-print: https://psyarxiv.com/bv5mp

introduction

Humans process the identity of familiar faces more robustly than unfamiliar faces (i.e., the **familiar face advantage**) (Bruce et. al, 1999; Jenkins et. al, 2011)

A recent article claimed human face expertise is limited to familiar faces (Young and Burton, 2018)

They developed a model of familiarity effects but underestimated human unfamiliar face recognition (GFMT; model *d'*=1.65, human *d'*= 2.58) and required human landmarking, making it a questionable model of human unfamiliar face recognition (Kramer, Young, Burton, 2018)

What does it mean to say we are experts at (unfamiliar) face recognition?

automaticity and **high performance**? (Young and Burton, 2018)

based on a **wealth of experience**? (Diamond & Carey, 1986; Gauthier et. al, 1997)

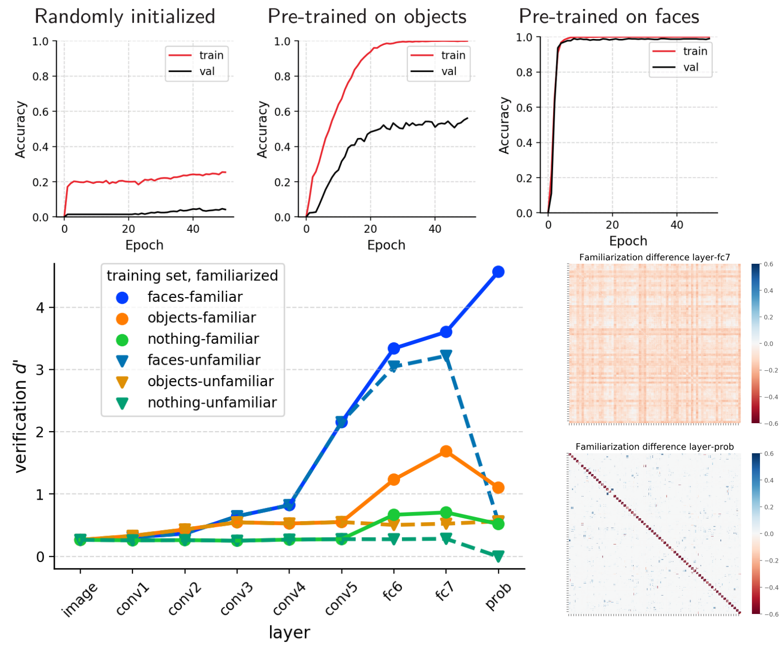
Our **proposal**:

Humans bring to bear a large amount of visual experience in achieving impressive but imperfect performance in the **ill-posed task** of unfamiliar face recognition

Large **within-identity variability** and between-identity similarity implies that some idiosyncratic experience is necessary for maximal performance

Unfamiliar and familiar face perception rely on a **largely shared mechanism,** which is fine-tuned to individual faces for accurate familiar face recognition

how does prior experience influence face processing?



Face domain experience allows for rapid/robust learning of new identities

It also allows for reasonable verification of unfamiliar faces at deep layers

Familiarity results in a sharp verification gain in the probability layer

Familiarity assimilates matching pairs but hardly affects non-matching pair distances

comparing humans and DCNN

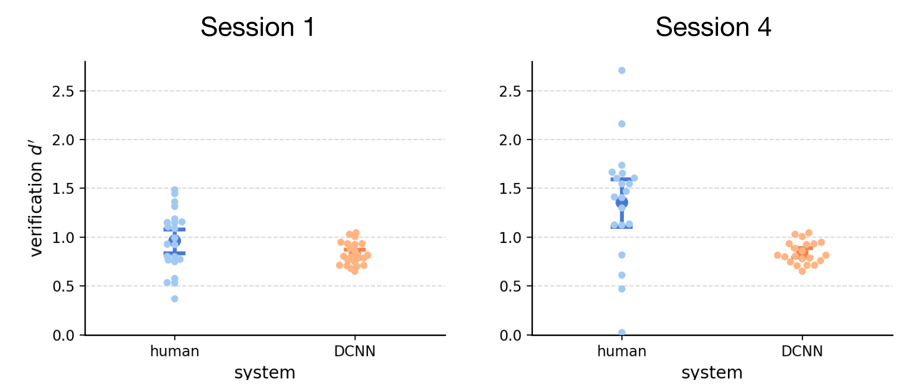
Select challenge match/non-match image pairs with VGG-Face (Parkhi et. al, 2014) (no overlap of training data with our modified VGGFace2 dataset)

For each subject, select 200/1000 hardest match+non-match pairs

task: simultaneous-pres. face verification with 1-7 similarity rating (10 s/trial)

Repeat same 400-trial sequence for up to 4 sessions per subject (n=21)

Test face-trained DCNN on same pairs, before and after familiarization

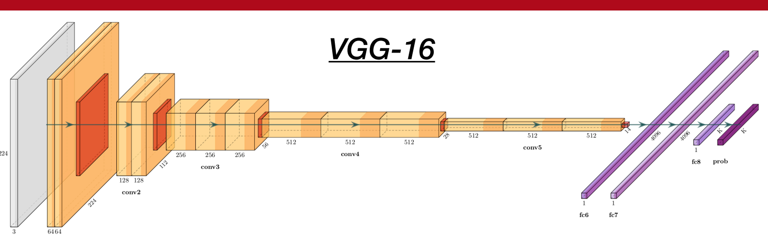


Humans marginally better than DCNN in session 1 (mean *d'*=0.96 vs. 0.83; p=0.084)

Humans do even better with unsupervised experience (mean *d'*=1.35; p=0.0004)

DCNN representation is sufficient for perfect familiarized verification (not shown)

computational approach



Simulations of deep convolutional neural network (DCNN) (Simyonan & Zisserman, 2014)

Vary pre-training distribution content (objects, faces, nothing)

size-matched subsets of **ImageNet** (objects) and **VGGFace2** (faces)

For faces, also vary fraction of total VGGFace2 database used

Fine-tune FC layers on identification in **Labeled Faces in the Wild** (familiarization)

Test **verification** before/after **familiarization**

References

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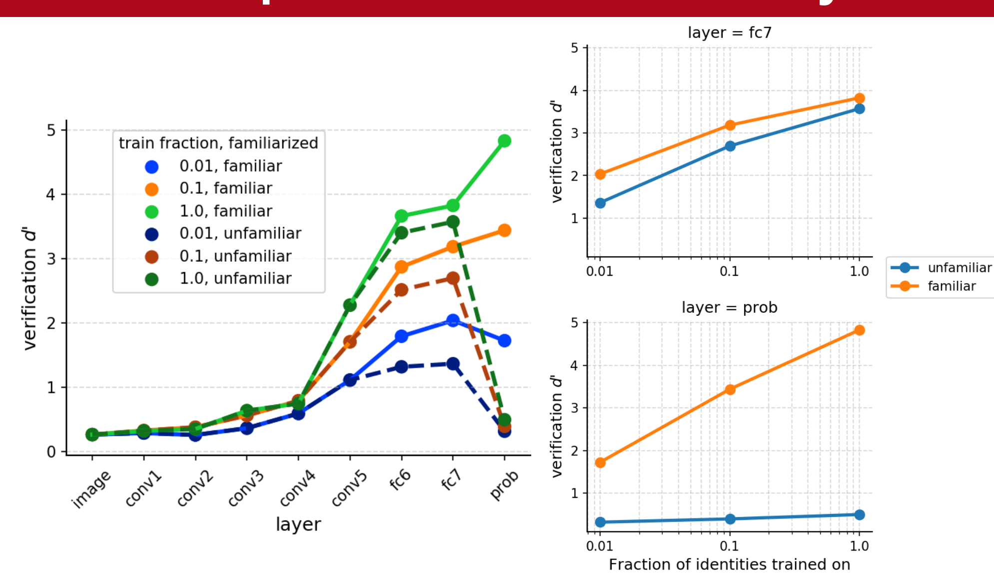
how much prior face experience is necessary?



Prior experience with more identities improves both unfamiliar and familiar verification

Log-linear relationship without obvious plateau; greatest slope for probability layer

conclusions

Human-level performance on unfamiliar face recognition requires a high-level representation, and seems to depend on a large body of experience learning generic face variability

Familiarization allows for the assimilation of perceptually different images of the same individual to a common representation

- Reliably doing so from limited data requires accounting for generic face variability (i.e. through prior learning)

The familiar face advantage in verification may be interpreted as follows:

- **Unfamiliar** face identity verification -> **high-level perceptual matching**
- **Familiar** face identity verification -> **identity matching**
- When identification is good, identity matching is much more robust than perceptual matching, even for familiar faces

Acknowledgments

Thanks to Mike Tarr and the viscog group at CMU for helpful discussions

Funding to attend this conference was provided by the CMU GSA Conference Funding