VISUAL EXPERTISE AND THE FAMILIAR FACE ADVANTAGE

Nicholas Blauch, Marlene Behrmann, David C. Plaut
Neuroscience Institute and Department of Psychology, Carnegie Mellon University
blauch@cmu.edu | behrmann@cmu.edu | plaut@cmu.edu

Carnegie Mellon University
Neuroscience Institute

Cognitive Computational Neuroscience CCN

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)

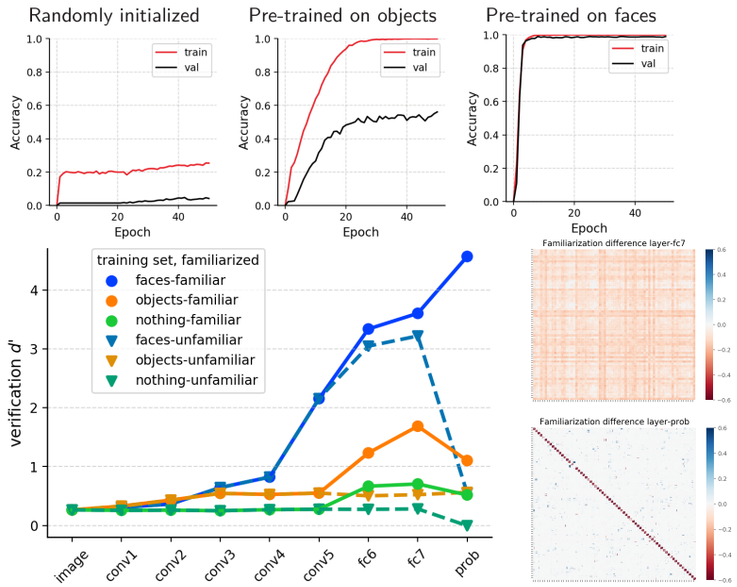
Our **proposal**:

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

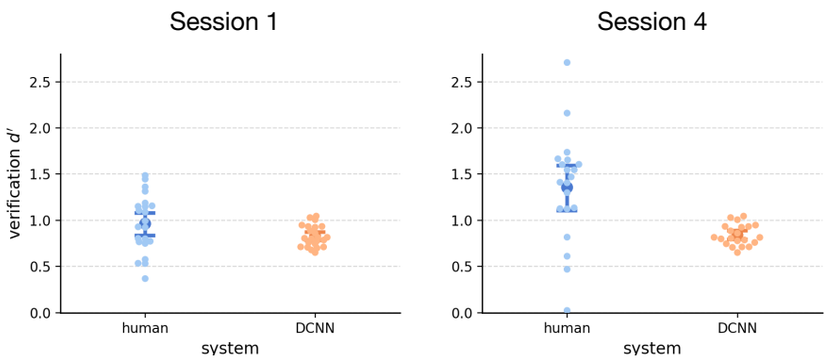
how does prior experience influence face processing?



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

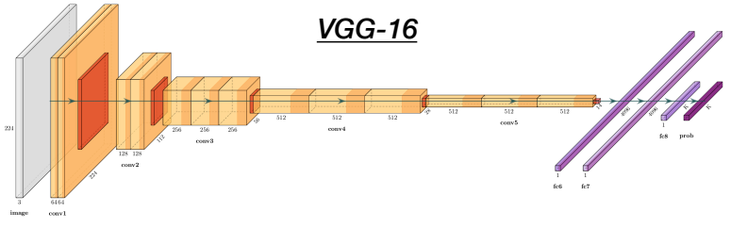
comparing humans and DCNN

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



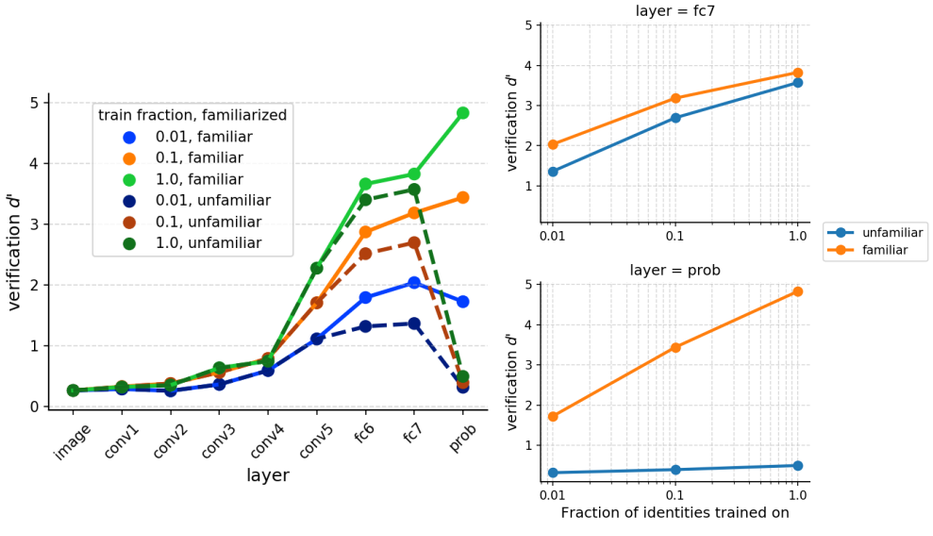
Humans marginally better than DCNN in session 1 (mean *d'*=0.96 vs. 0.83; p=0.084)
Humans do even better with unsupervised experience (mean *d'*=1.35; p=0.0004)
DCNN representation is sufficient for perfect familiarized verification (not shown)

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**

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

References

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Acknowledgments

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