

Functionally localized representations contain distributed information: insight from simulations of deep convolutional neural networks

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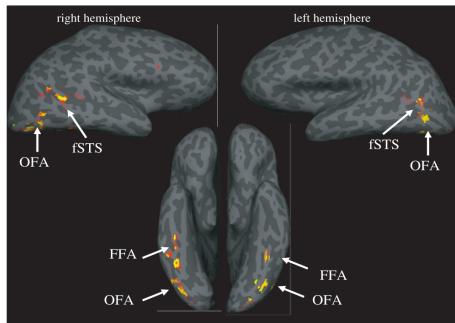
Rosie A. Cowell
David E. Huber

Big question for this talk

Is the neural basis of face recognition distinct from that of general visual recognition?

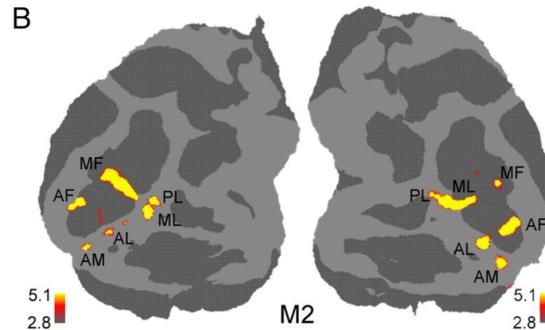
Functional localization of face processing

Human cortical regions selective to faces
(faces > objects, $p < .00001$)



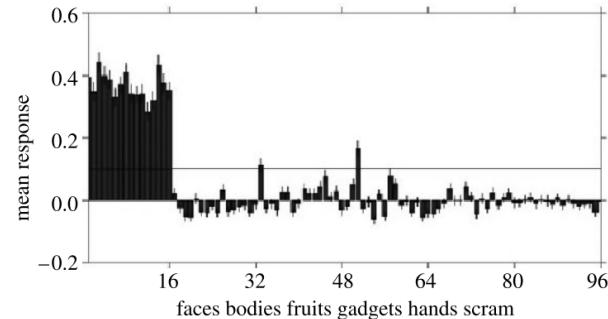
Kanwisher & Yovel, 2006

Macaque monkey "face patches"
selective to faces vs. objects



Tsao, Moeller, Freiwald 2008

Macaque face patches show enhanced
mean neural response to faces



Tsao, Freiwald, Tootell & Livingstone, 2006

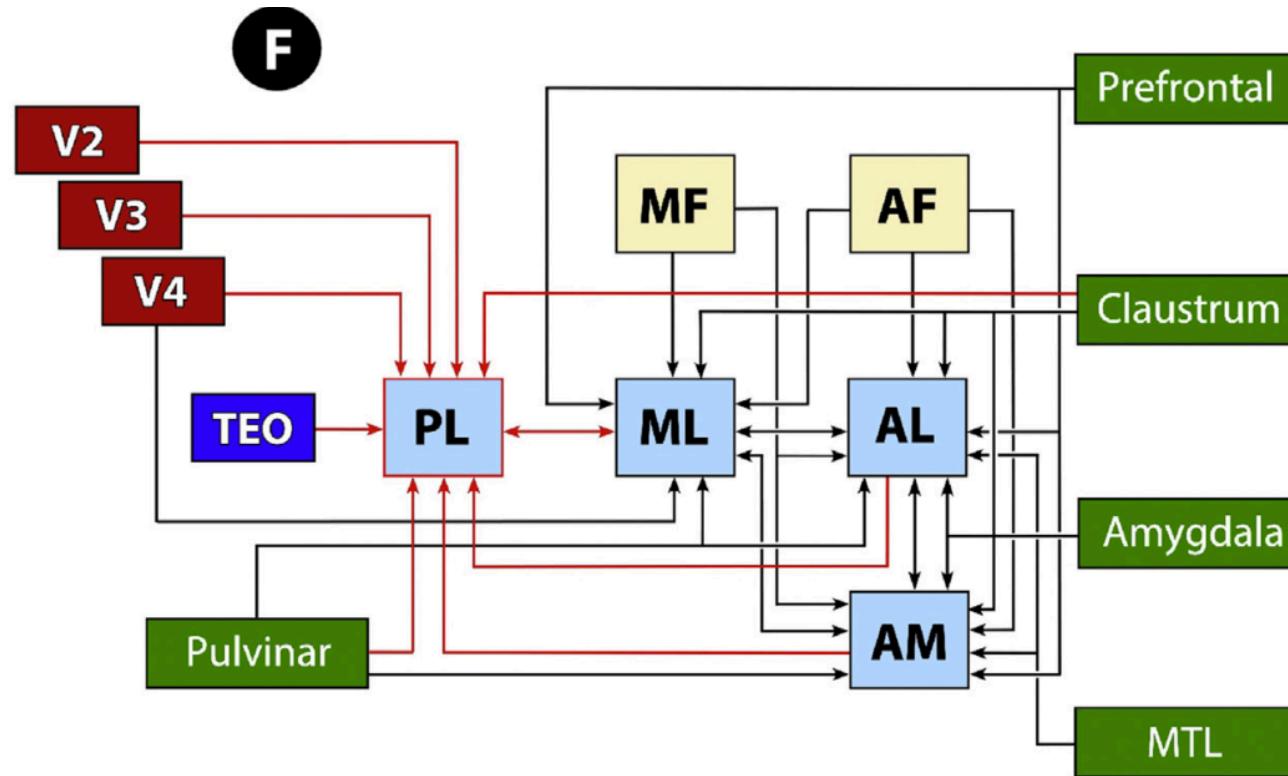
Face selectivity exists in stable locations in macaques as early as 200 days and overlaps with foveal and curvature selectivity present in the first postnatal weeks (Livingstone et. al, 2017; Arcaro & Livingstone, 2017)

Face selectivity seems to be driven by low-level features and refined by perceptual experience recognizing faces

Tracer injections in face patches reveal greater connectivity with each other than other nearby regions
(Grimaldi, Saleem, Tsao, 2016)

-> functional sub-hierarchy honed by evolution?

Proposed wiring diagram of a functional sub-hierarchy for face processing



Grimaldi, Saleem, Tsao (2016)

Are face-selective regions just part of a distributed code?

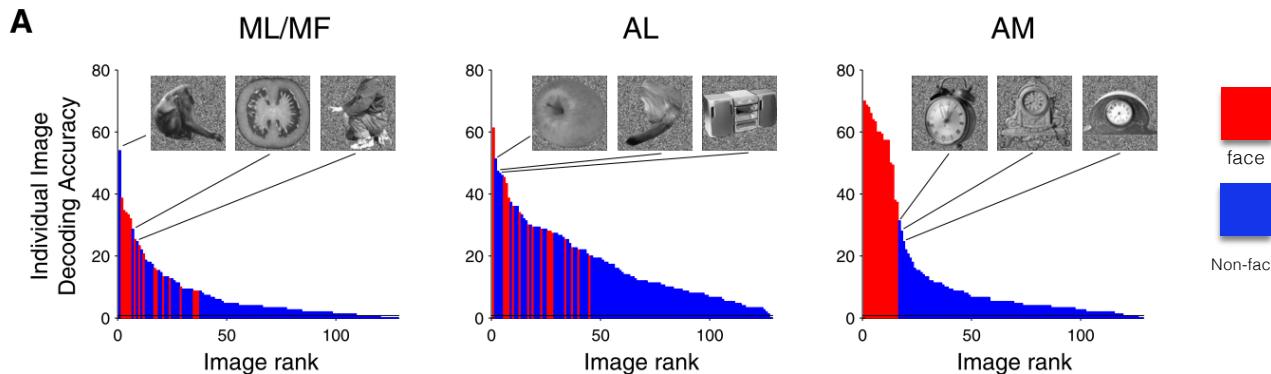
Multivariate pattern analysis (MVPA) of human face-selective areas supports non-face discrimination, and MVPA can discriminate faces without face-selective areas (Haxby et. al, 2001)

MVPA of all macaque “face patches” supports discrimination of most non-face images (Meyers et. al, 2015)

However, there are clear advantages for faces, especially in the most anterior patch AM

Seems unlikely that processing in face selective areas is a full-fledged module gated by earlier face-detection (e.g. Tsao & Livingstone, 2008)

Preferences in mean firing rate and information suggest a form of un-gated “specialization” or marginal “modularity”

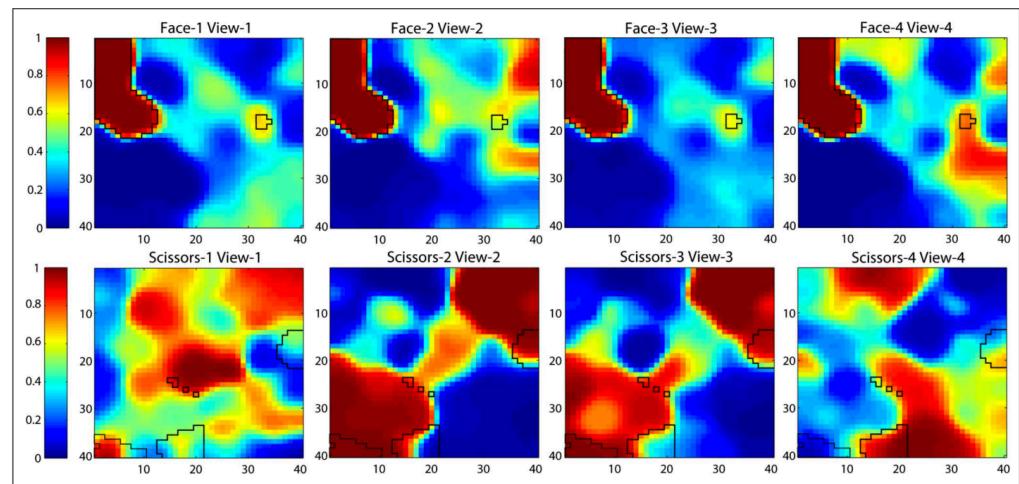
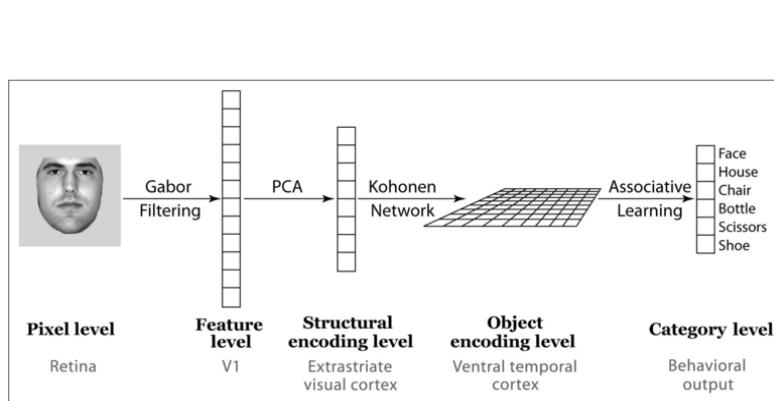


Meyers et. al, 2015

A model of distributed representation produces face-selectivity

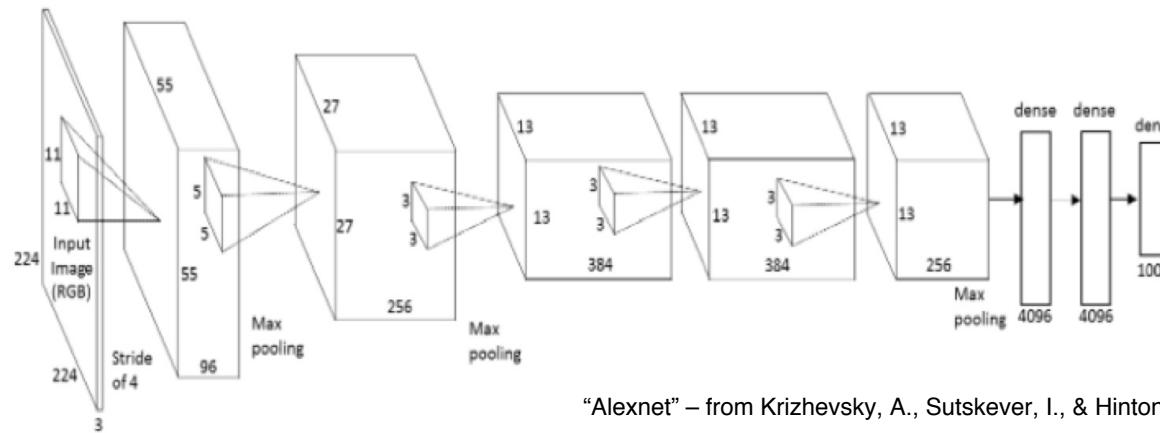
Visual representations stored in a **domain-general** self-organizing Kohonen grid naturally develop strong view-independent face preferences compared to other categories (Cowell & Cottrell, 2013)

- However this model cannot perform face individuation – all individuals look basically the same!
- Not constraining to individuation belies the need for specialized circuitry for faces above other object categories for which individuation is less important



Cowell & Cottrell, 2013

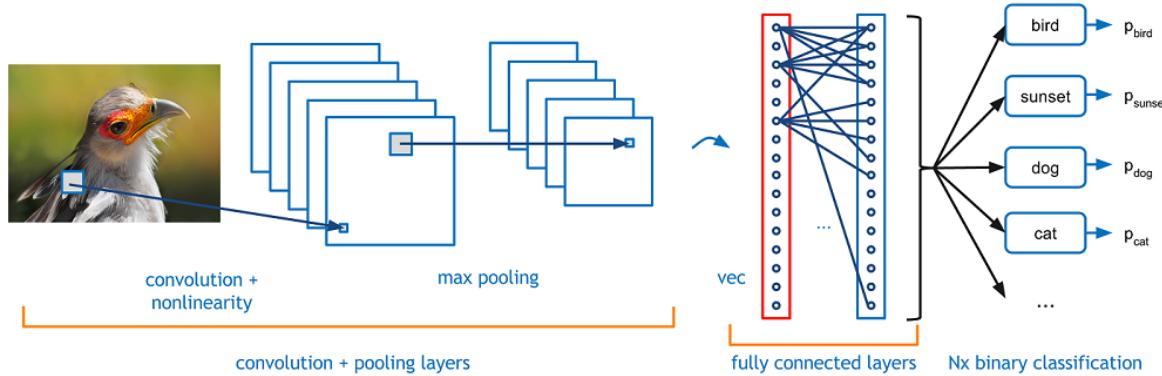
Deep convolutional neural networks can perform human-level object recognition and face individuation



"Alexnet" – from Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012).

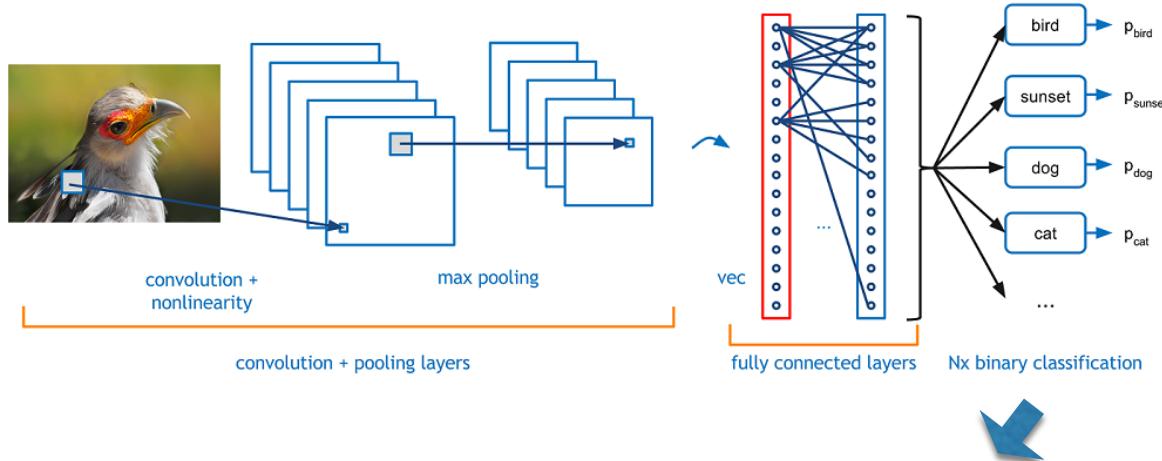
- Do functionally localized DCNN representations yield category-distributed information?

Deep convolutional neural networks for visual categorization



- DCNNs are the state-of-the-art in computer vision applications relating to high-level visual knowledge, such as categorization
- They consist of a hierarchy of processing layers and learn features through training on millions of images
- DCNN representations provide the best fits of neural data related to object recognition (Yamins et. al, 2014; Güclü & van Gerven, 2015)
- Impressive behavioral achievements, biological-inspiration, and ability to predict neural responses make them a powerful class of models for cognitive science

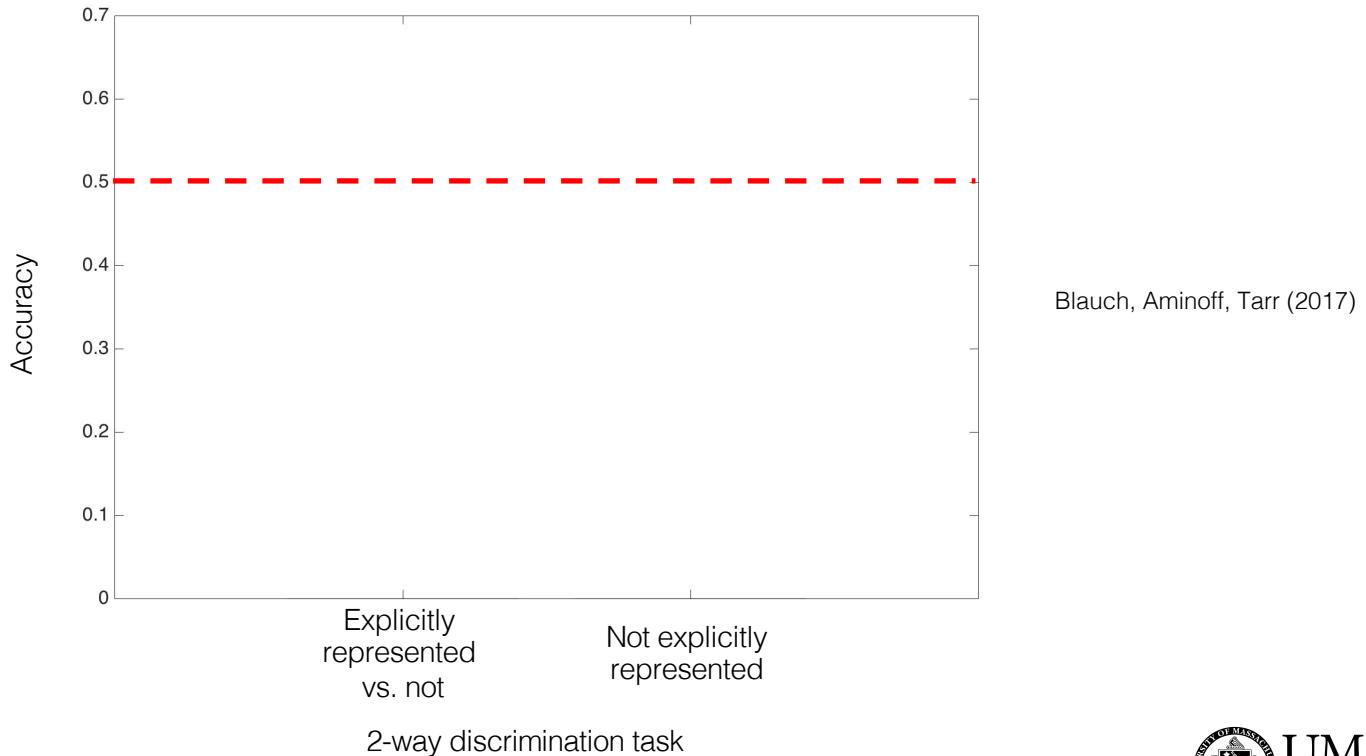
Deep convolutional neural networks for visual categorization



How much information do **localized categorical representations** contain about other categories?

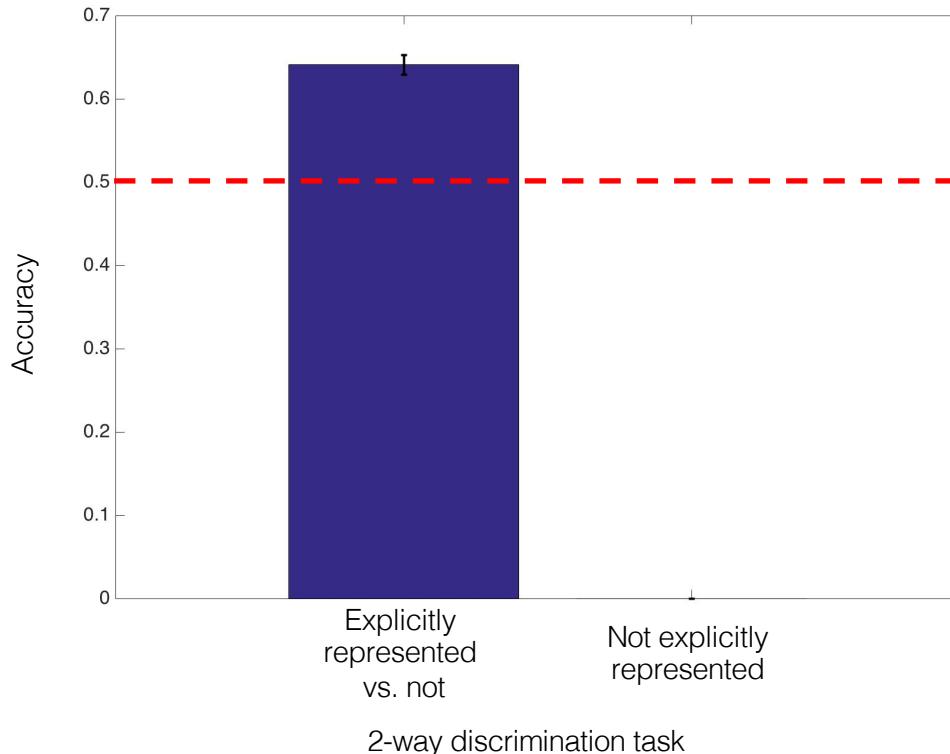
Results: decoding single-unit localized categorical representations in Alexnet

Using 10-fold (80% training) cross-validated SVM classification with
bootstrapped pairs across a sample of 20 ImageNet categories



Results: decoding single-unit localized categorical representations in Alexnet

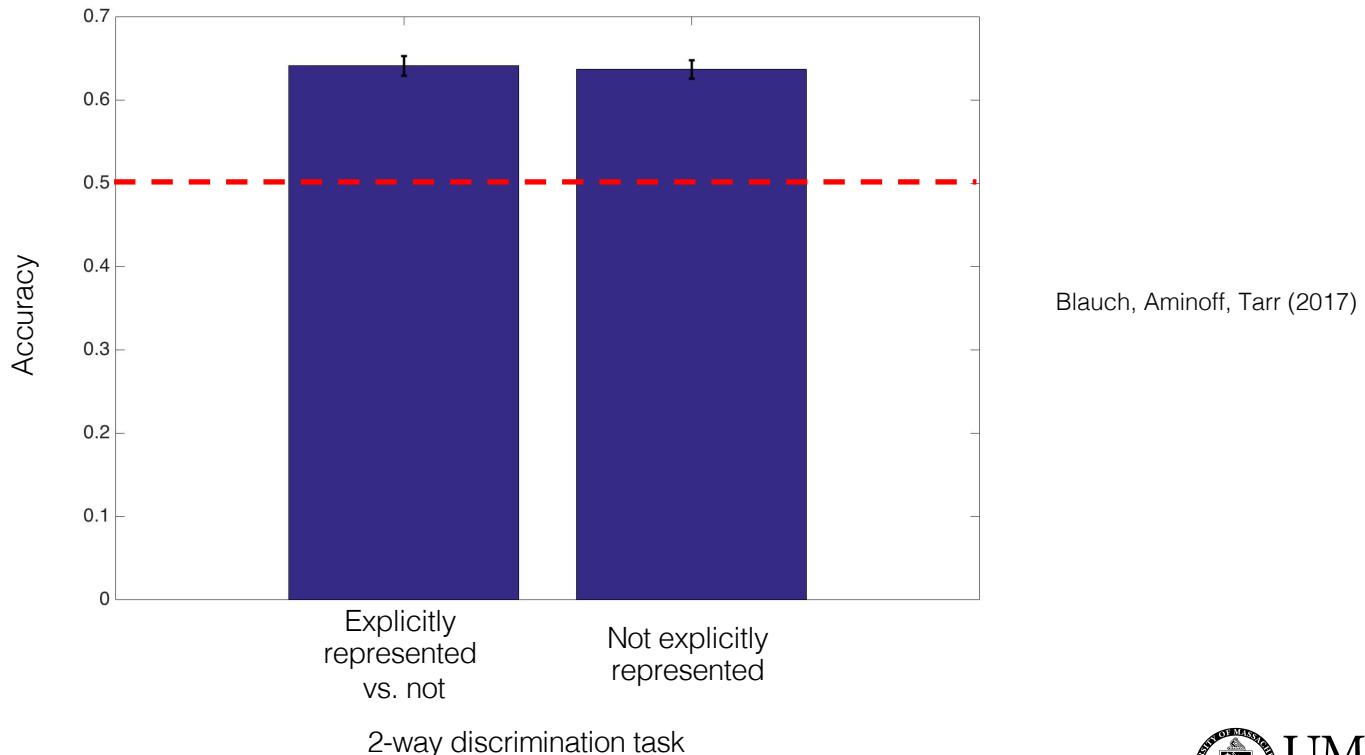
Using 10-fold (80% training) cross-validated SVM classification with
bootstrapped pairs across a sample of 20 ImageNet categories



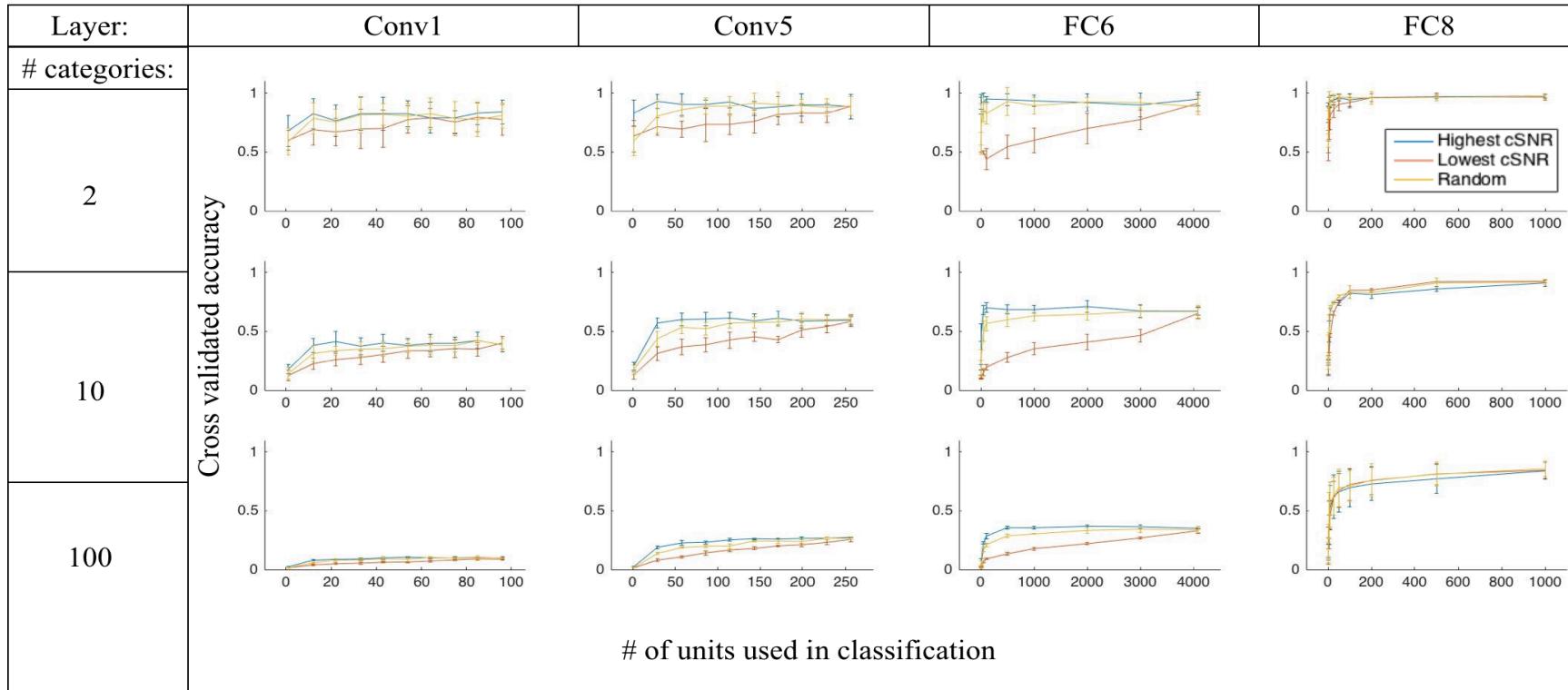
Blauch, Aminoff, Tarr (2017)

Results: decoding single-unit localized categorical representations in Alexnet

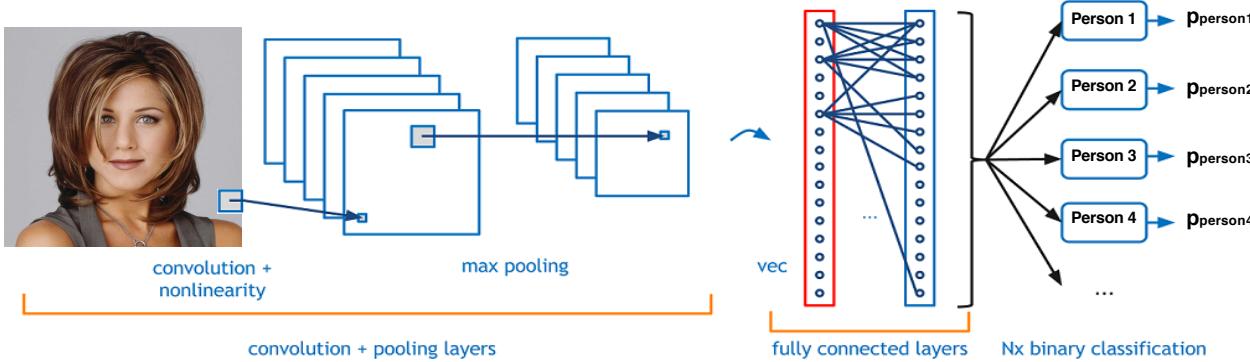
Using 10-fold (80% training) cross-validated SVM classification with
bootstrapped pairs across a sample of 20 ImageNet categories



Decoding populations of units across layers in Alexnet

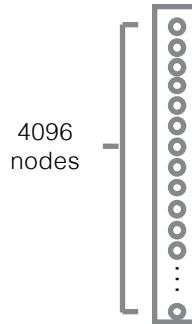


DCNNs for face individuation



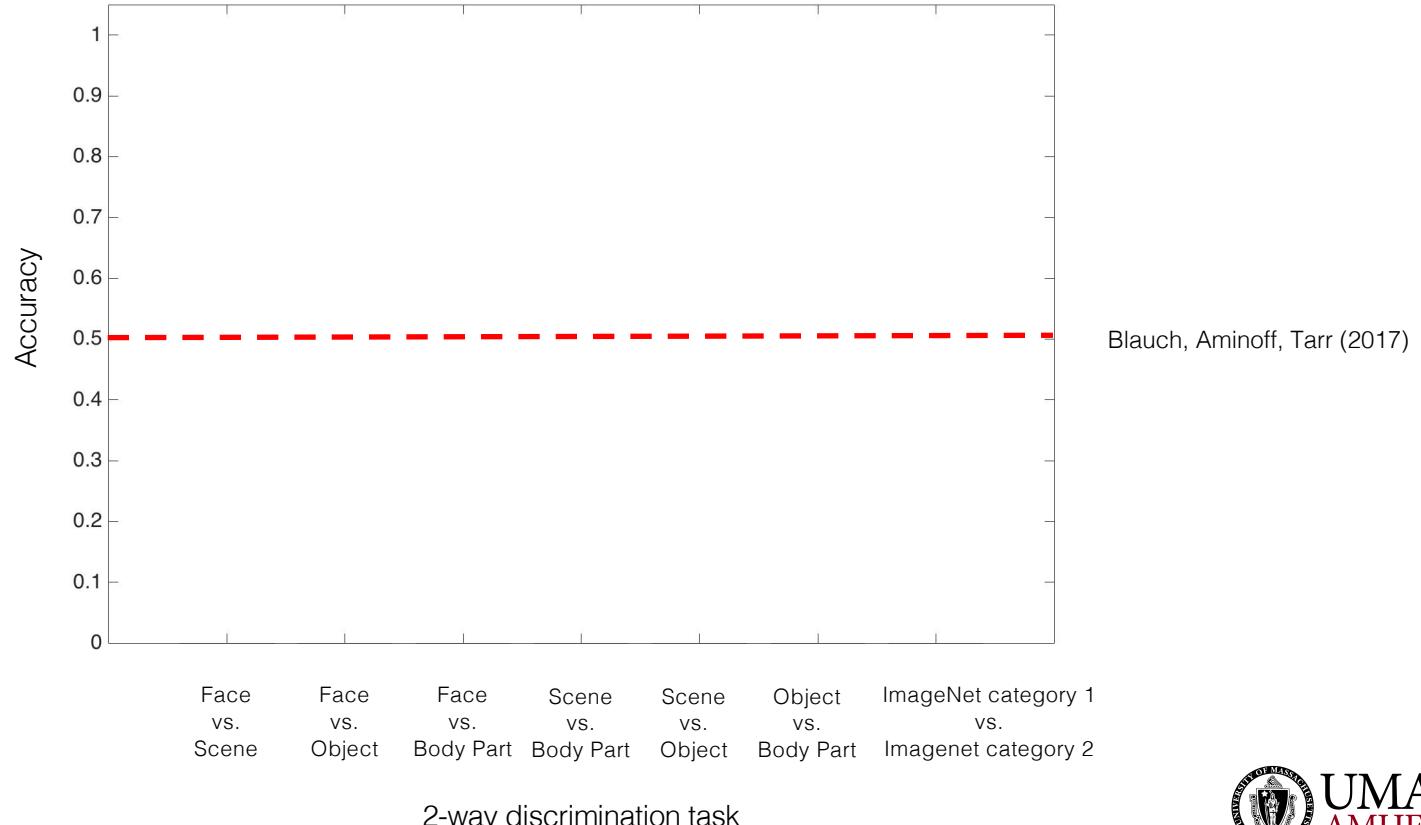
A computational face “module”

- **VGG-face** is a state-of-the-art DCNN for face individuation, trained to individuate 2622 faces at >90% accuracy (Parki, Vedaldi, and Zimmerman, 2015)
- The last fully-connected layer contains 4096 high-level features trained specifically for face individuation
 - We use these representations as a model of high-level face-specialized representations, e.g. a “modular” hypothesis about FFA or face patch AL



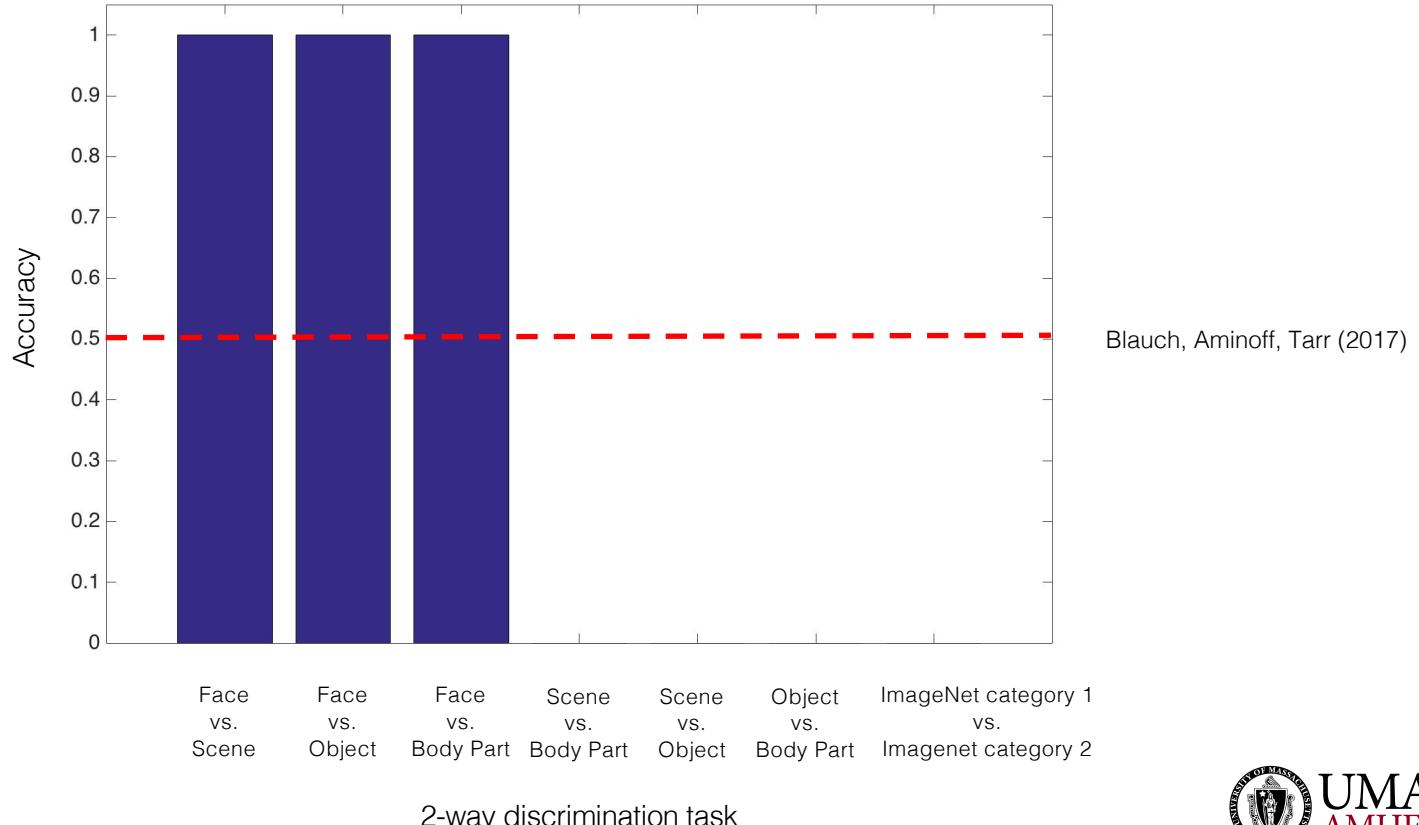
Results: decoding a computational face module

Using 10-fold (80% training) cross-validated SVM classification



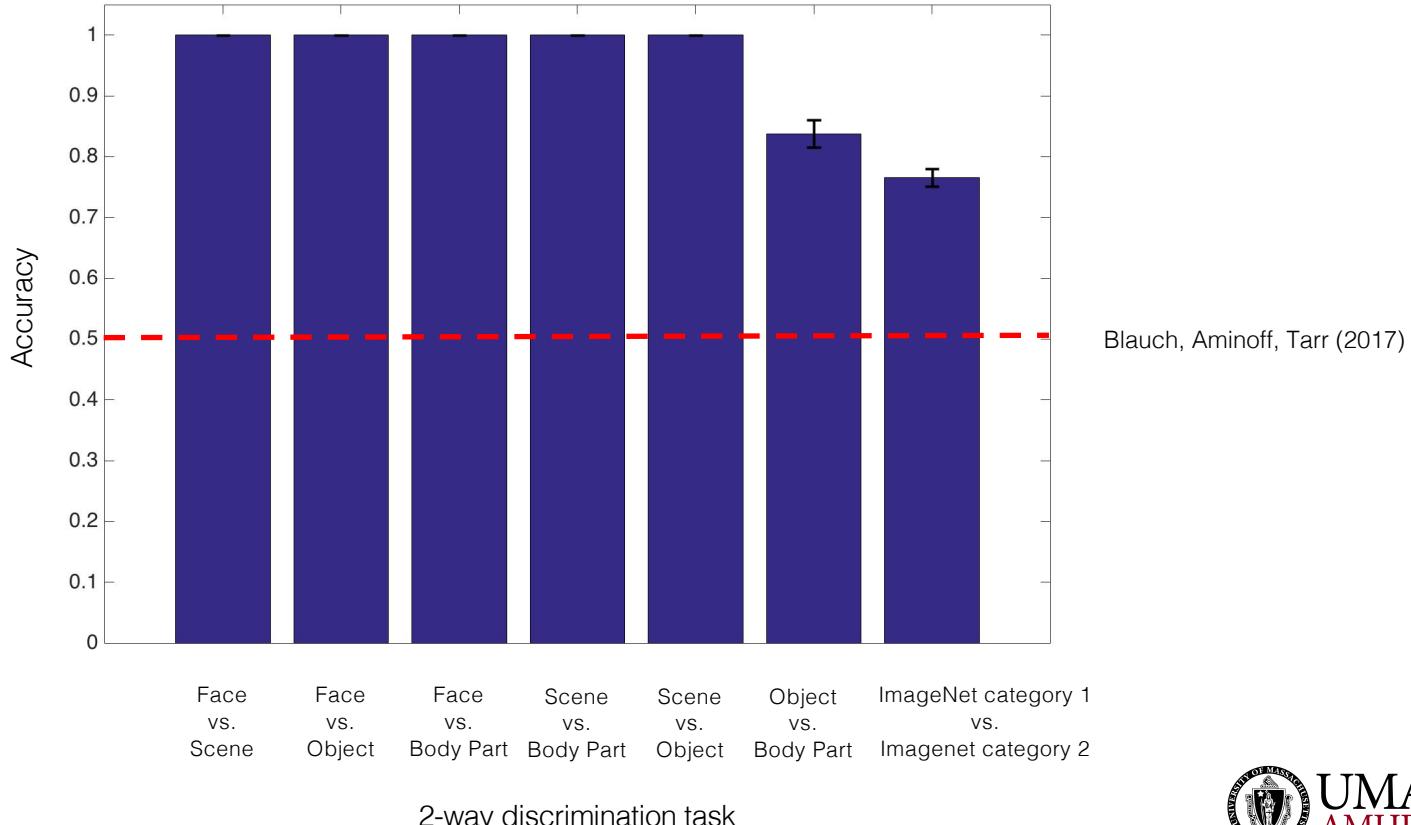
Results: decoding a computational face module

Using 10-fold (80% training) cross-validated SVM classification



Results: decoding a computational face module

Using 10-fold (80% training) cross-validated SVM classification



Conclusions

- The brain is highly selective for visual faces (e.g. Kanwisher & Yovel, 2006)
- Face-selective areas seem to still process non-face inputs (Haxby et. al, 2001; Meyers et. al, 2015)
- A **distributed topographic representation** produces the characteristic evidence of functionally localized activation (Cowell & Cottrell, 2013) but is shallow and cannot perform face individuation
- We show that deep **functionally localized representations** sufficient for human-level object categorization and face individuation produce categorically distributed information
 - Information can be deceiving! Information != function. Must build models to get at function.
- Current neuroscience evidence is thus consistent with both distributed and localized processing of faces
- Due to behavioral requirements and stimulus properties, we suspect that the true face processing scheme is moderately modular – containing patches highly specialized/trained for faces but not formally gated and thus adaptable to visual experience

Discussion: the origins of functional localization of face processing

- Self-organizing principles lead to face-selectivity based on within-category feature similarity alone (Cowell & Cottrell, 2013)
- Innate face looking preference (e.g. Johnson et. al, 1991; Reid et. al, 2017) creates input bias, causing greater tuning to faces. This preference may be mediated by innate subcortical circuitry (Johnson, 2005).
- Regularization over connection length leads to greater modularization (Clune, Mouret, Lipson, 2013)
- Expertise with individuating faces causes top-down refinement of face-selective circuitry (e.g. Tarr & Gauthier, 2000)
 - Could be the basis of face specialization, or face-specialization could be the basis of other categories of expertise eliciting high activation in FFA (e.g. birds, greebles, cars)
 - Finer-grained representations developed for face recognition may be usefully coopted for other face-like categories requiring expertise
- Next steps – build models to test the behavioral and “neuroscientific” effects of these various factors

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Thanks!

Questions?