Density of Top-Layer Codes in Deep Convolutional Neural Networks Trained for Face Identification

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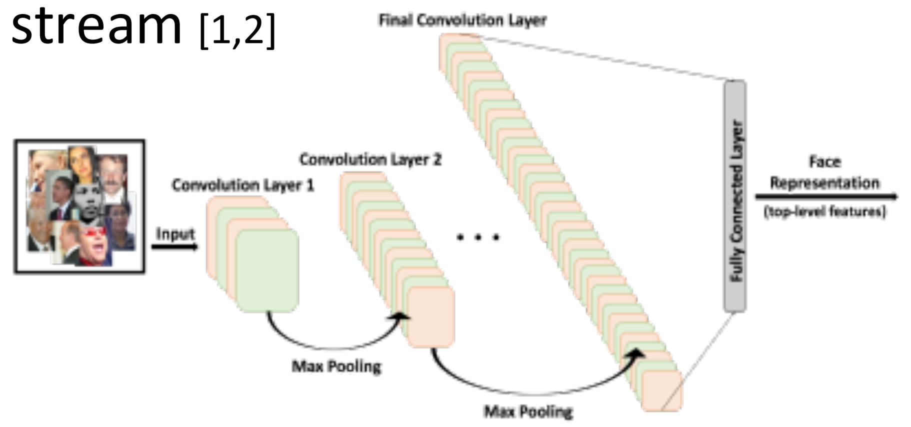
Deep Convolutional Neural Networks (DCNNs)

- Robust across image conditions (view, illumination, etc.)
- Modeled after primate ventral visual stream [1,2]
  - Early layers -> V1
  - Intermediate layers -> V4
  - Final layers -> IT [3,4]



- Image information (e.g, viewpoint) retained despite identity training [5]
- Distribution of information in top-level code?
  - Identity, gender (subject variable) [6], viewpoint (image variable) [5]

Features in Primate Visual System

- Low-level visual features retinotopic & semantically interpretable (e.g., edge detectors) [7]
- Face identification -> high-level vision, categorical codes [8]
  - Link between visual receptive fields and features less clear
- Categorical representation of faces not well understood
  - Neurons tuned to features [9]
  - CNNs "directions in a space" interpretable/meaningful features [10]

Goal

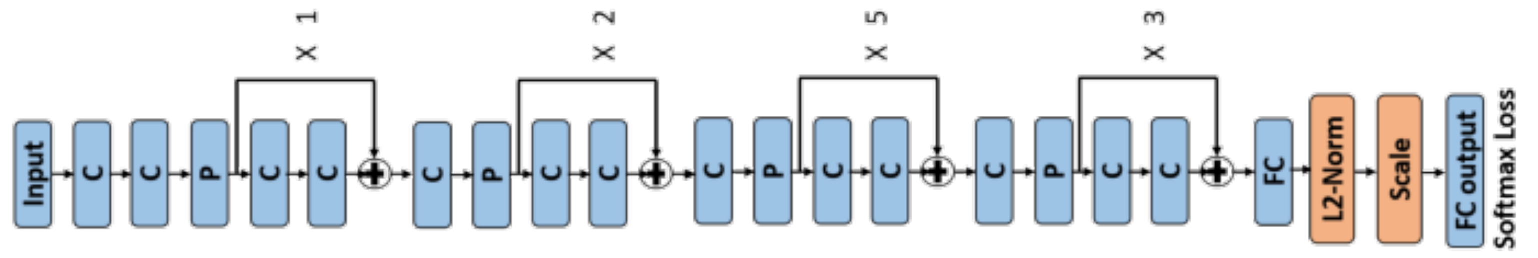
Probe distribution of identity, gender, viewpoint across individual units in DCNN top layer

Approach

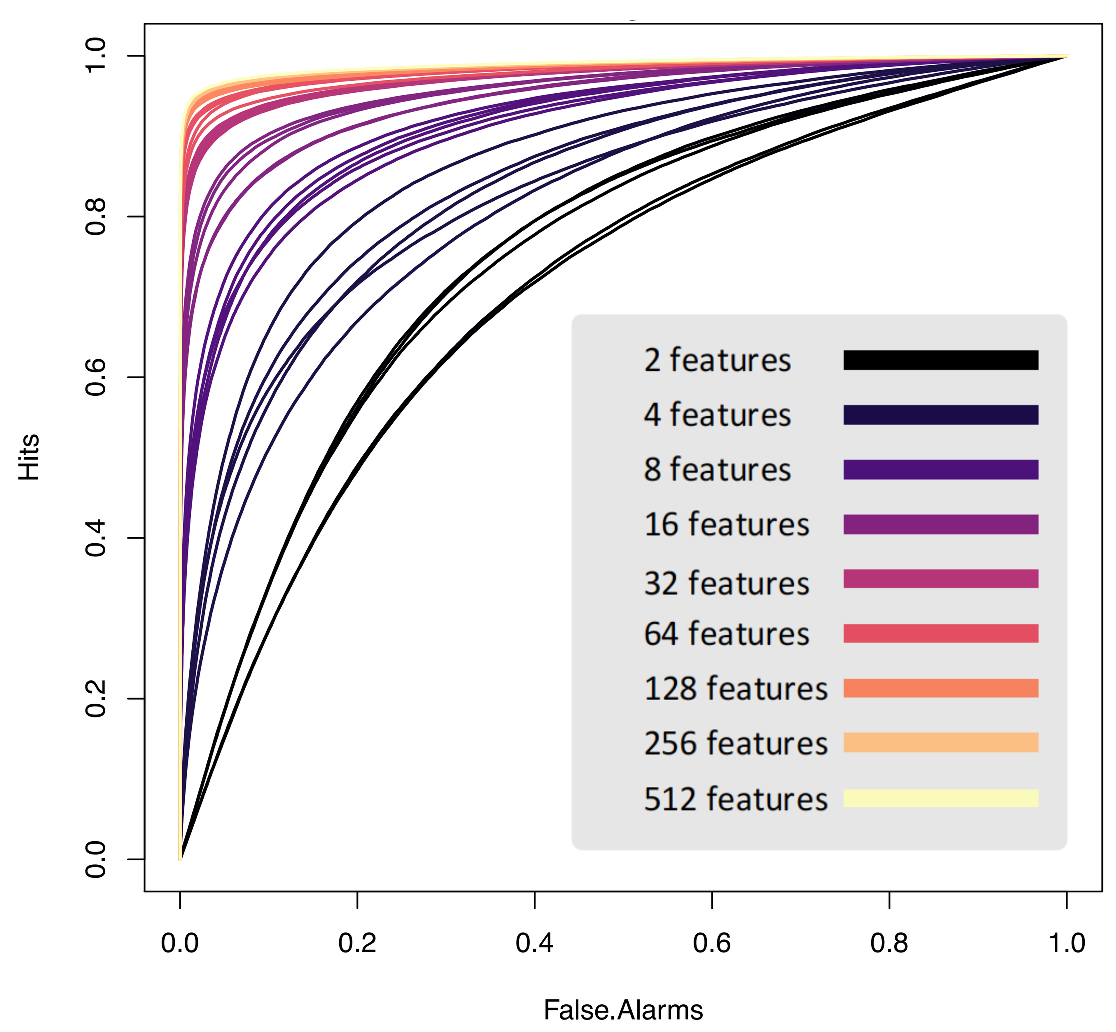
- Random feature deletion
- Re-evaluate identity, gender, viewpoint information in subspaces of varying dimensionalities

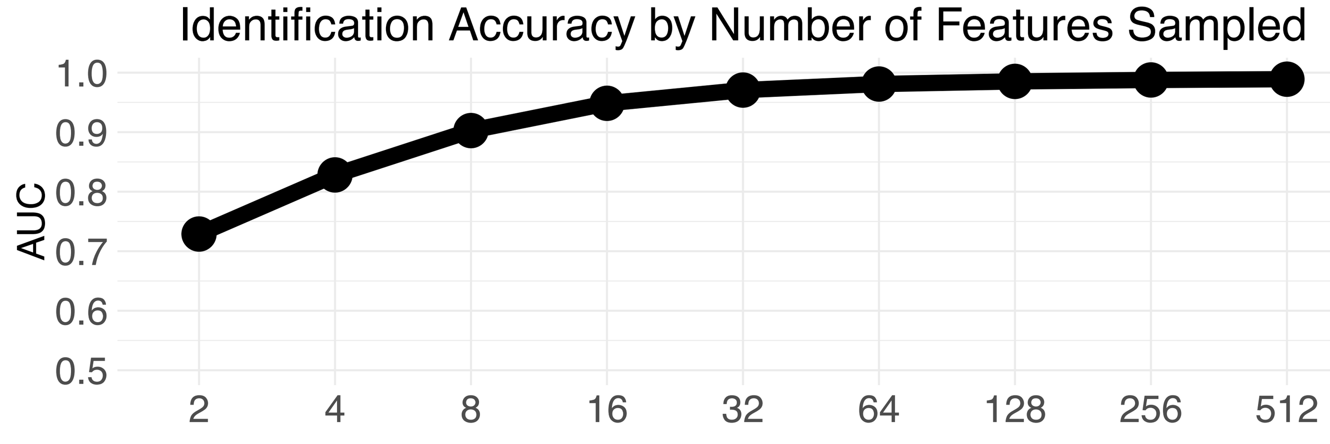
Network

- High-performing face identification network [11]
  - 101 –layered ResNet [12], trained on nearly 6 million images of 58,000 identities
  - 512-dimensional final output representation



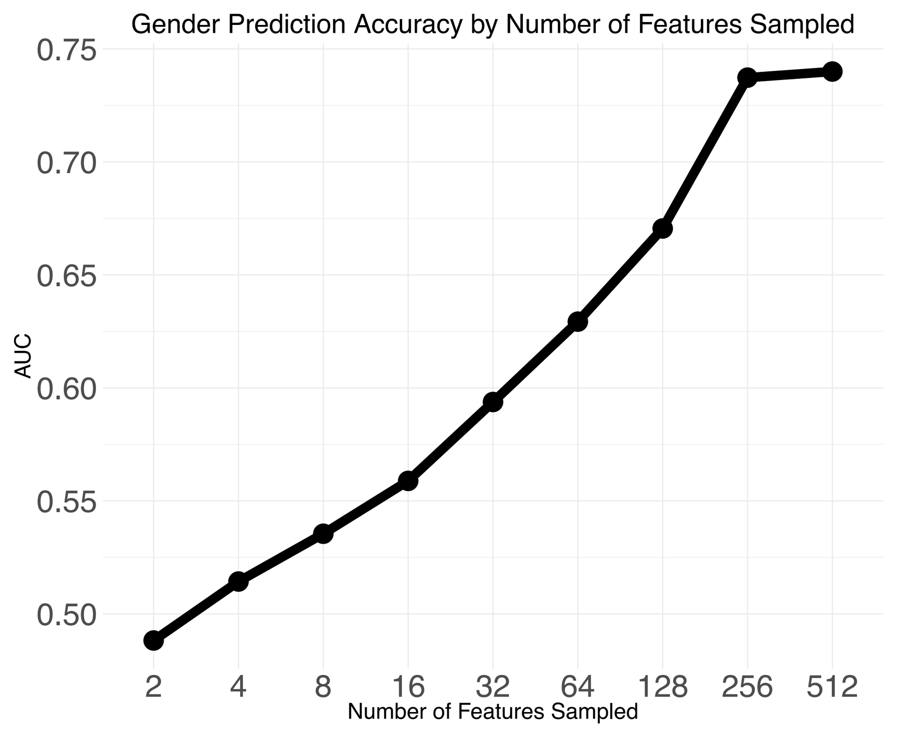
Subspace: Identification





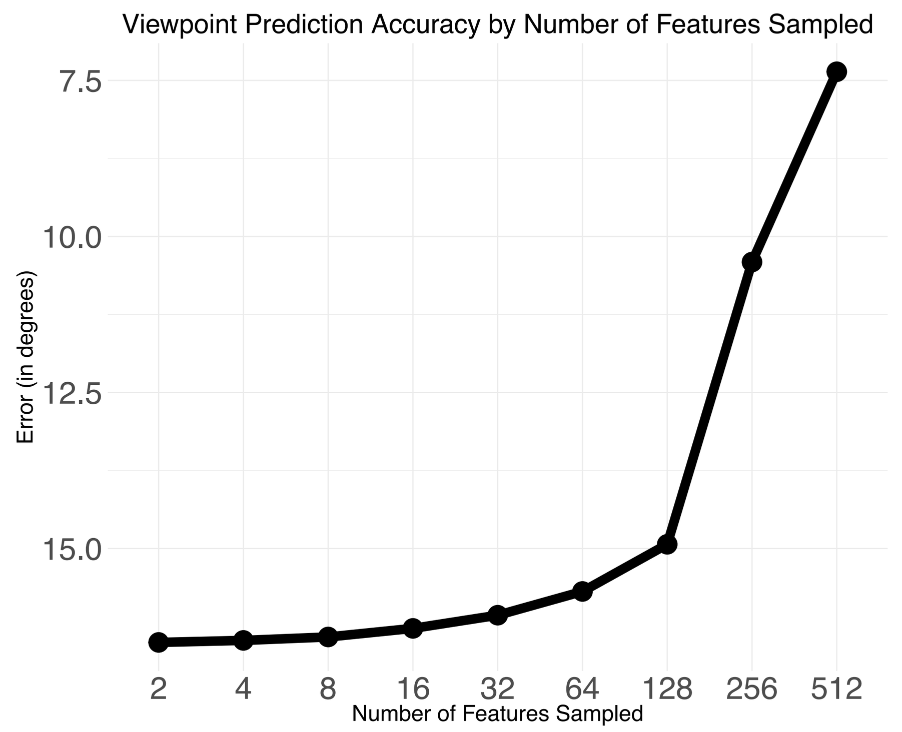
- Identification accuracy maintained when sampling very few randomly chosen features

Subspace: Gender



- Gender prediction accuracy decreases gradually with size of sampled features

Subspace: Viewpoint



- Viewpoint prediction accuracy declines sharply when fewer features sampled

Methods

- randomly sampled sets of features from output representation
- computed ROC curves of each sample on face-identification, gender classification, and viewpoint prediction tasks using the "in the wild" IJB-C dataset [13]
  - > 141,332 images, 3,531 identities

Conclusions

- Top-level feature units spread identity information efficiently
  - All units contain identity information, random combinations of units lead to good performance
- Coding of gender and viewpoint make sense in context of [6]
  - Hierarchy of clustering according to identity/image variables
- Robust code for face identity
- Many sources of identity information, many solutions

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