Understanding neural representations in early visual areas using convolutional neural networks

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Motivations
- Convolutional neural networks (CNNs) have feature representations like those in higher layers of the primate and human visual cortex (Agrawal et al., 2014; Khaligh-Razavi & Kriegeskorte, 2014; Yamins et al., 2014).
- Recent data on V1 neurons suggested they may encode much more complex features (see poster 798.03 / Y7).
- CNN might be a useful tool to understand the encoding of complex features in lower layers (V1/V2) of visual cortex as well.

Images and neural data
- 286 V1 and 390 V2 neurons in 2 monkeys to 150 stimuli using multi-electrode arrays.
- The 150 stimuli have 3 subsets of 50: Edge (E), Appearance (A), and Exemplar (EX), in levels of increasing complexity.
- Around 3000 V1 neurons in 3 monkeys to 2250 natural images, using calcium imaging (see poster 798.03 / Y7).

Computer vision models
- CNN “AlexNet”
  - conv1
  - norm1
  - pool1
  - 6 other layers
  - pool5
  - fc6
  - fc7

Model comparison using Representational Similarity Analysis
- RSA (Kriegeskorte et al., 2008) was used to compare model and neural representations $\phi_{\text{model}}$ vs. $\phi_{\text{raw}}$ (area can be V1, V2 etc.).
- Similarity between representations is defined as the Spearman’s rank correlation coefficient of their representational dissimilarity matrix (RDMs), each of which captures pairwise distances between images for a given representation.

Results
- Bottom right: all CNN layers on the 2250 stimulus set.
- Horizontal lines estimates the achievable similarity by computing the similarities of feature representations among different monke
- Diverse filter shapes. V1likeSC and pool1 are better than V1like, especially on complex stimuli (EX).

Neuron matching and visualization
- Single neuron matching results were consistent with RSA. V1 matched better to pool1, V2 to pool2.
- Complex stimuli (EX) shifted to higher layers compared to simple stimuli (E). V2 neurons were also more correlated to higher layer CNN units than V1 neurons.
- While some neurons have visualizations consistent with the existing literature (a, b, c, e), some neurons preferred more complex features (d, f).

Why CNN performs better
- Network effects. Without normalization and pooling, V1like performed worse (not shown).
- Diverse filter shapes. V1likeSC and pool are better than V1like partially due to learned diverse filters compared to Gabor ones in V1like.
- Network architecture might contribute as well. On the 2250 stimulus set, higher CNN layers performed better than lower layers even with all network parameters being random.

Conclusion
- Some V1/V2 neurons may encode more complex features than previously thought.
- CNN is a good approximate model for understanding and visualizing V1 and V2 neurons.
- Future work: (1) add more biological constraints into CNN models to make CNN explain neural data better, (2) explore CNNs with heterogeneous layers, each layer with units of different complexities.

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