Predicting Complex Cell Behavior Using Deep Predictive Models

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Introduction & Significance

Seeking to understand the underlying principles of computations in visual system, previous studies have devoted effort in different approaches including building deep neural networks (DNN) to predict neuronal response patterns in primary visual cortex of both primates and rodents[1,2,3,4]. Several studies have developed DNN models predicting neuronal responses to natural images at high accuracy. However, high performance in predicting neuronal performance does not necessarily guarantee that the model utilize the same computation as the neuron.

In this project, we plan to test if a CNN model accurately predicting a complex cell model to different stimuli could learn the computation of a complex cell and develop similar tuning and invariance property.

Our work solve a core concern for modeling neurons with DNN: if similarity in responses implies similarity in computation. Our results demonstrate that a model with good performance captures the computation of the neuron, opening the possibility of studying neuron computation in neuronal data driven DNNs.

Material & Method

Material:

In this project, we build a convolutional neural network and train it with 5000 images from ImageNet as shown in Figure 1.

Network logistics:

Our convolutional neural network is developed in Pytorch 1.3 and Python 3.6. The input elements to the network is image vectors and the output elements predict responses generated by a complex cell model.

Complex cell model:

The complex cell model is implemented as the motion energy model, which fully captures the two characteristics of complex cells: direction tuning and phase invariance (shown in figure 4).

Running environment:

Training takes about 8 mins on a workstation with NVIDIA 2080Ti GPU and Intel i7-9700K CPU.

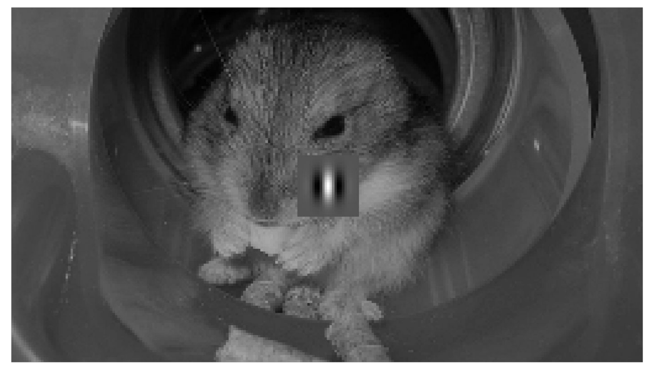


Figure 1. An example of natural images from ImageNet and the receptive field of the complex cell.

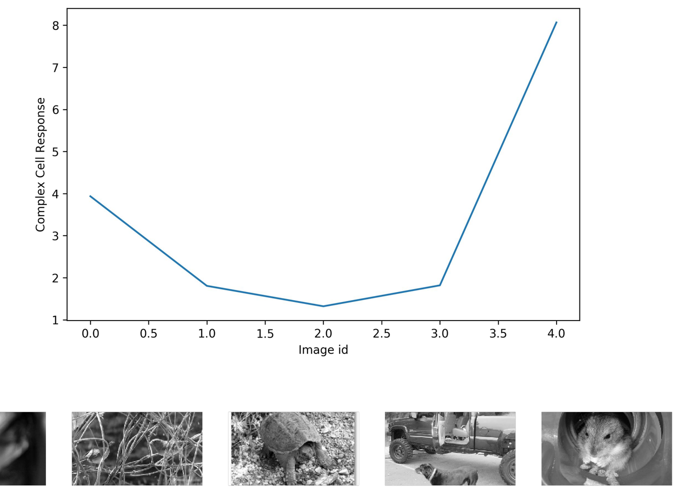


Figure 2. Examples of complex neuron's response to different images

CNN and Complex cell model

In the CNN for this project, the input are gray scale image matrices with the size of 144*256 from ImageNet. Every image are also the input for the complex cell model and output with a continuous value representing the intensity of the cell firing. The convolutional network are trained with this value for every image and the goal is to predict complex cell model's response to novel images.

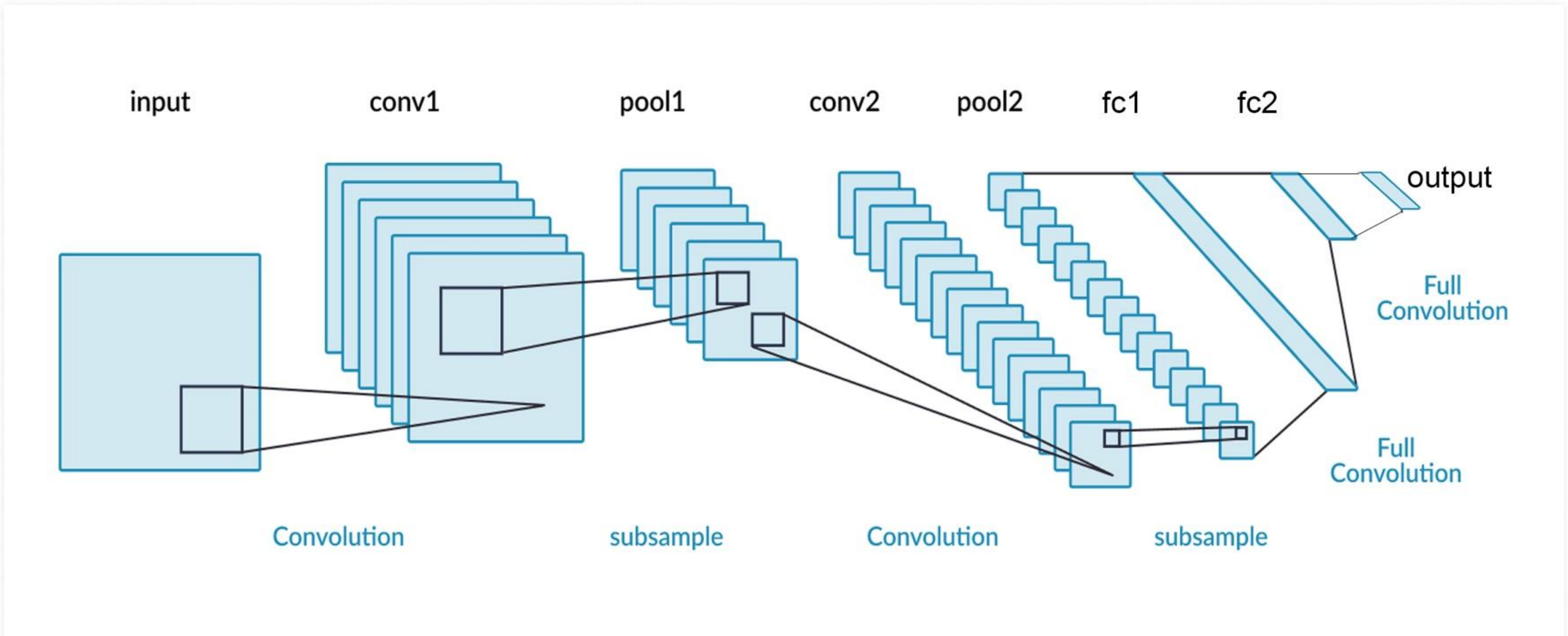


Figure 3. Structure of the convolutional neural network

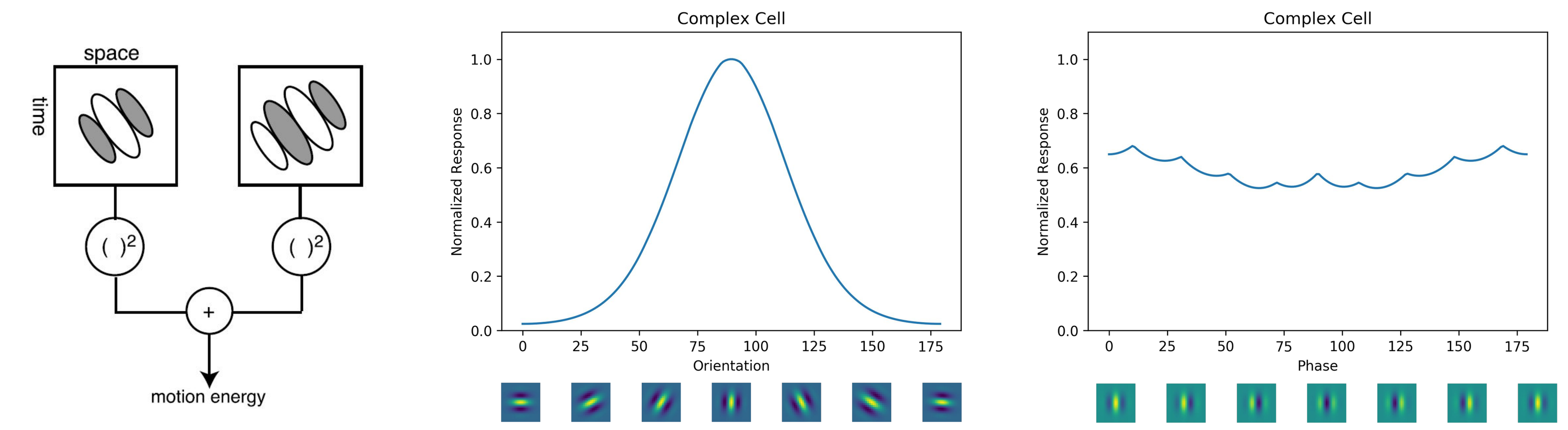
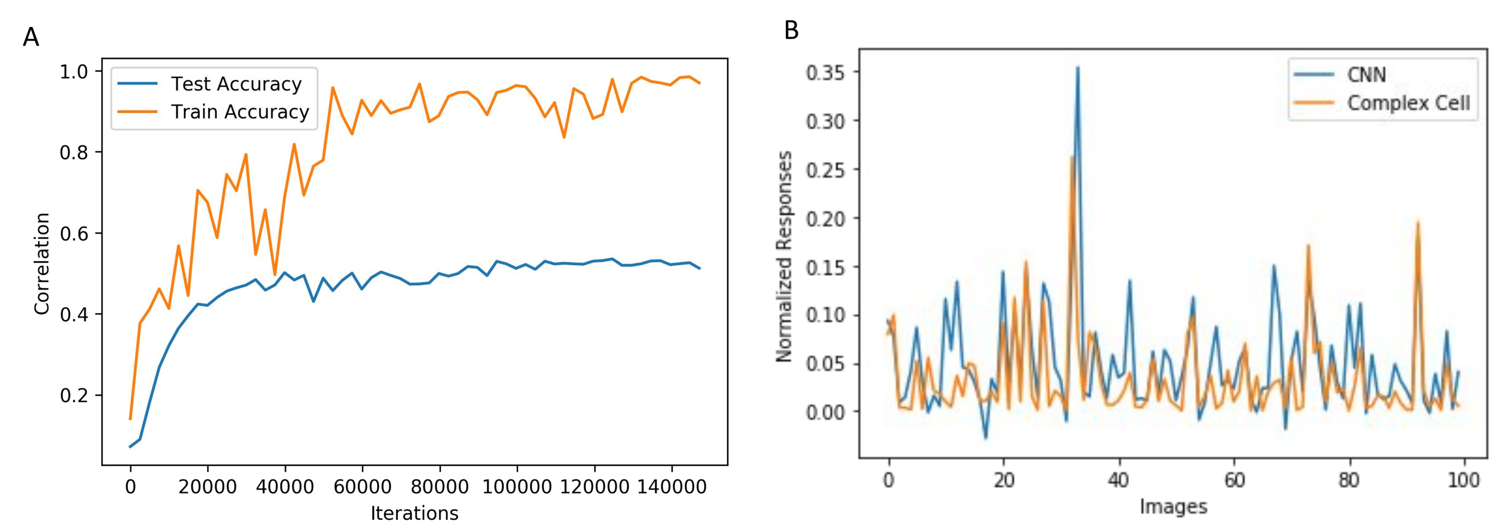


Figure 4. Complex cell model. Left: structure of complex cell computation. Middle: tuning property of complex cell to stimuli orientations. Right: tuning property of complex cell to stimuli phases

Results



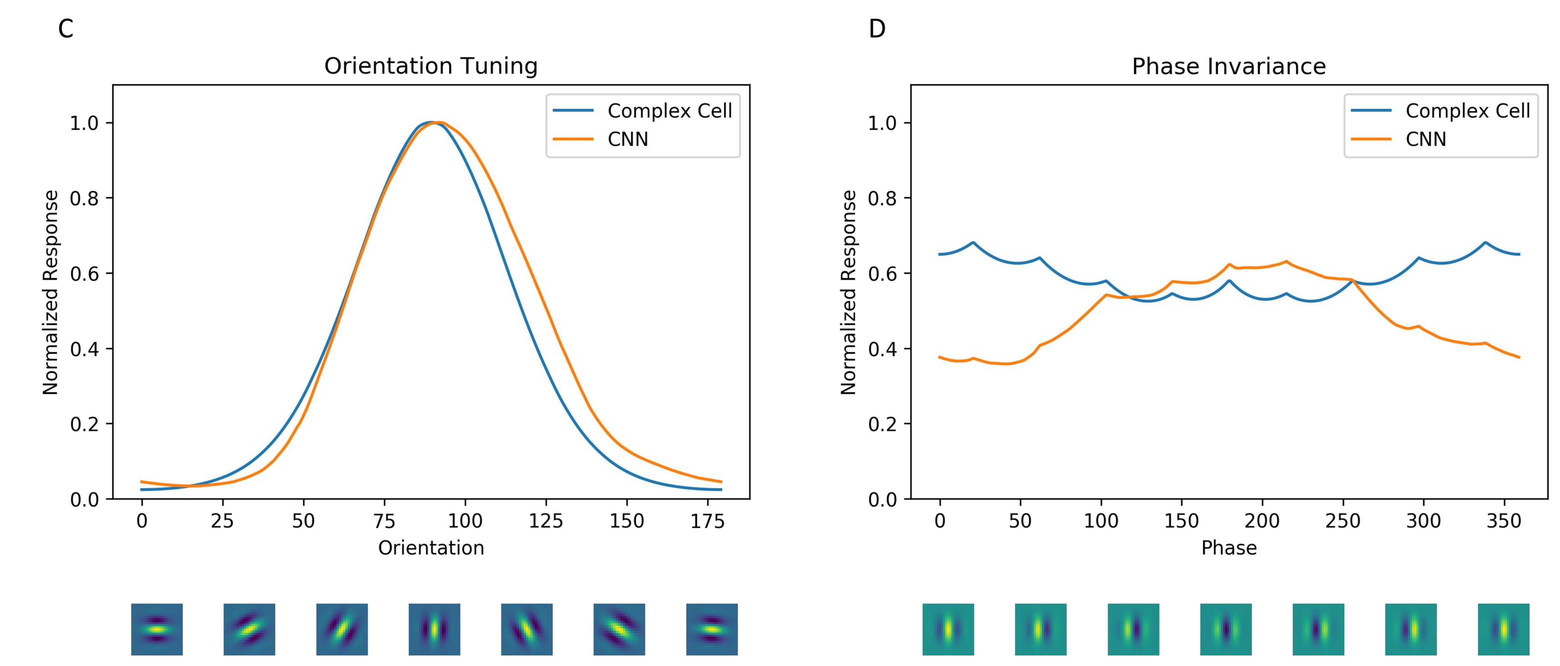


Figure 5. A: CNN training and testing accuracy with iteration number. B: CNN and complex cell's response to images within a patch. C: comparison between CNN and complex cell on tuning properties to stimuli orientations. D: comparison between CNN and complex cell on tuning properties to stimuli phase

Discussion

In this project, we've demonstrated that a CNN model could predict a complex neuron's response to novel stimuli with a reasonable performance. Moreover, it's able to capture the computational characteristics of a complex neuron such as orientation and phase tuning.

However, it is not clear how the orientation tuning and phase invariance is achieved in the CNN.

One possibility is that the CNN model might be just mimicking the motion energy model, or it alternatively utilized a totally different computation to achieve similar effects.

The significance of current work is that it allows us to investigate the inner computation mechanism underlying similar responses. One future direction would be looking into the computation of the CNN model through feature visualization techniques.

Conclusions

In this project, we trained a CNN to predict a complex cell's response to novel natural images based on a complex neuron model. We were able to:

1) predict the complex neuron's response at the accuracy of around 0.5
2) capture the orientation tuning property of the complex neuron
3) capture the phase tuning property of the complex neuron

References

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