**Significance**

The brain has approximately 100 billion neurons that have diverse connectional and functional properties1. While it would be impossible to understand what computations each individual neuron does, we can simplify this problem by classifying neurons into different cell types with similar morphology, physiology and molecular profiles. This strategy has allowed us to summarize what populations of neurons do into simple principles. For example, Purkinje cells in the cerebellum perform error detection, parvalbumin interneurons are crucial for excitation/inhibition balance, and midget cells in the foveal retina process discrepancies between shades of red and green. Cell types play a central role in our current understanding of systems neuroscience, which is why it is important to understand why neurons are organized into different cell types. To answer this question, we will study a model system, the retina, using efficient coding to understand how having different cell types improves the processing of information.

Many features of the retina make it an excellent system to study why neurons form different cell types. The retina has a clear laminar structure, allowing neurons to be classified based on their layer. The deepest layer of the retina has photoreceptors which transform light into electrical activity. This information gets sent forward to bipolar cells, followed with retinal ganglion cells (RGCs), which respectively form the intermediate and superficial layers of the retina. Another advantage of the retina is that we have direct control over the inputs of the system. This allows us to map the receptive field of each neuron, which can also be used to classify neurons into cell types. This is especially useful for retinal ganglion cells, which are separated into three main types: parasol, midget and bistratified cells. Other than having different morphologies, these cell types process distinct– but complementary – information. Parasol cells process increments and decrements of lights, while midget cells process discrepancies between red and green, while bistratified process increments in blue light. Most cell types within the retina are known to form mosaics, having non-overlapping neurons that tile the entire retina. These mosaics are unlikely to happen by chance, which means they can also be used as a criterion for classification of neurons into different cell types. Overall, this means that the retina processes information in parallel across multiple different cell types, with each cell type responsible for encoding one characteristic of natural images across the entire visual field.

Because a lot has been discovered about cell types in the retina, this system provides us with a unique opportunity to understand why neurons are organized into cell types. A normative explanation of retinal cell types would consist of simple assumptions and normative principles that would describe what computations neurons perform, and from which cell types would naturally emerge. Efficient theory is the best set of normative principles to achieve this, as it is the most prevalent theory in the retina. Efficient coding states that early sensory systems form an efficient neural code that decorrelates its inputs to maximize information with a limited number of spikes available. Early theoretical work on efficient coding explained how the center-surround organization of RGCs arises from decorrelation, both for achromatic and for color inputs2, 3. They managed to do so with very simple assumptions, such as gaussian inputs, a linear model that allows negative firing rates, and an infinite number of neurons. However, these simple assumptions did not manage to account for the formation of mosaics or the segregation of neurons across different cell types.

Recent work from our lab leveraged machine learning to make efficient coding predictions with natural image inputs, a limited number of neurons and linear-nonlinear models. These new assumptions allowed us to replicate ON and OFF mosaics, and suggested that the anti-alignment between the two can be explained by a high noise level within RGCs. Previous work from the lab has also showed that it is efficient for neurons to encode either high spatial or high temporal frequencies, but not both, similar to midget and parasol cells. This new type of efficient coding model raises the possibility of asking whether efficient coding can explain why – and how – RGCs are segregated into different cell types. In this project, we will investigate whether efficient coding can replicate (1) How different RGC types process chromatic information and (2) How different RGC types process motion. We will then do in-silico experiments to understand what properties of efficient coding or natural images makes it possible – or not – for the normative model to replicate experimental findings.

**Innovation**

**Technical innovation:** To complete either aims, I will need to develop new machine learning techniques to train efficient coding models with multiple correlated channels (cones or latencies), which implies increasing the number of parameters by multiple folds. I will solve this overparameterizing problem by designing new methods to parametrize receptive fields across color channels and latencies. By doing so, we will pave the way for future research to solve efficient coding problems with very larger number of parameters.

**Conceptual innovation:** Most of the efficient coding research in vision involves a single input channel that is encoded by a large number of neurons. However, neurons in the retina have multiple correlated input channels, such as different colors and latencies. This project is conceptually innovative because I consider efficient coding models with multiple correlated channels. By doing so, we will learn how efficient coding models handle correlated channels, and whether this solution is similar to the computations RGCs perform.

1. Zeng, H. and J.R. Sanes, *Neuronal cell-type classification: challenges, opportunities and the path forward.* Nature Reviews Neuroscience, 2017. **18**(9): p. 530-546.

2. Atick, J.J. and A.N. Redlich, *Towards a theory of early visual processing.* Neural computation, 1990. **2**(3): p. 308-320.

3. Atick, J.J. and A.N. Redlich, *What does the retina know about natural scenes?* Neural computation, 1992. **4**(2): p. 196-210.