One of the primary goals in neuroscience is to figure out simple principles that explain how systems are organized. Barlow (1961) proposed one of the most successful theories in neuroscience, which states that sensory systems should remove redundancies in their inputs to optimize the information they process. This *efficient coding hypothesis* provides us with a mathematical framework to understand how neurons should encode information, which can then be verified experimentally. Efficient coding can explain many experimental findings in different sensory modalities such as vision, audition and touch (Lewicki, 2002; Miller et al., 2019). This hypothesis has been especially successful in the retina (Atick & Redlich, 1990), where many properties of retinal ganglion cells (RGCs) have been described by efficient coding. While early studies made simple assumption to solve problems that are analytically tractable, recent studies use machine learning to build efficient coding models with more realistic constraints (Karklin & Simoncelli, 2011). These new models have allowed more accurate comparisons between predictions from efficient coding and experimental data. Karklin & Simoncelli (2011) were able to explain why retinal ganglion cells separate into two different types – ON and OFF – which process light and dark information, respectively. They found that it was efficient for neurons within a type to encode distinct regions of visual space, repelling each other to form a ‘mosaic’ that tiles the entire retina. Such models were further expanded by my lab to explain more details about retinal physiology. We showed how efficient coding can explain why ON and OFF mosaics are anti-aligned (Jun, Field & Pearson, 2021), and why it is efficient for RGCs to encode low spatial with high temporal frequencies, and high spatial with low temporal frequencies (Jun, Field & Pearson, 2022).

To reduce redundancies, such efficient coding models encode discrepancies between their inputs. However, retinal ganglion cells have input channels, both across color channels (**Aim 1**) and across time (**Aim 2**), that are so redundant the discrepancy between channels contains little to no information. What are the efficient coding solutions for such scenarios is still unclear. To answer this question, this project will push the efficient coding hypothesis to its limits and test whether efficient coding can explain the receptive fields of RGCs with highly correlated channels. In **Aim 1**, we will investigate whether efficient coding can explain how RGCs integrate Long, Medium and Short cones to process color stimuli. In **Aim 2**, we will explain motion selectivity in the retina from efficient coding principles, which requires inferring how the spatial and temporal dimensions of receptive fields interact with each other.

**Aim 1:** Determine how RGCs should efficiently integrate redundant input channels

Hypothesis: The efficient strategy is to encode discrepancies between redundant channels

Retinal ganglion cells integrate inputs from cone photoreceptors, which are split into three different channels: Long (L), Medium (M) and Short (S) cones. The information in these three channels is mostly redundant, with most (~95%) of the information in natural images being achromatic. However, how the retina works seems to contradict that principle: Most RGCs’ responses are tuned to colors, with each neuron type processing a specific color channel. My project will reconcile these two principles and explain why encoding chromatic information is the optimal efficient coding strategy for natural images. To do so, I will build and train an efficient coding model to optimally encode chromatic natural images. This model will be similar to Jun et al. (2021) where each weight represents the input from a photoreceptor to a RGC. We omit bipolar cells because their contribution is thought to be roughly linear. These weights will then be optimized to maximize the mutual information between the natural images and the model RGC, within a limited firing rate constraint. Completion of this aim will allow us to understand why it is efficient for neurons to encode discrepancies between redundant input channels.

**Aim 2:** Determine how the retina should encode spatiotemporal correlations across inputs

Hypothesis: We can replicate how the retina encodes motion from efficient coding principles

Neuronal activity is not only correlated in both space and time, but spatial and temporal correlations also interact with each other. The most prominent example of this phenomenon is motion, where we can predict the future location of a moving object based on its current location and velocity. While it is clear that the efficient coding strategy for RGCs should include encoding motion, what exactly this strategy is – how many neurons should process motion and what should their spatiotemporal receptive fields be– is still unclear*. My working hypothesis is that the efficient coding strategy for encoding motion in natural images will replicate experimental findings about motion encoding in RGCs.* To answer this question, I will extend the previous spatiotemporal efficient coding model from my lab to be spatiotemporally inseparable; that is, the model will be able to learn a receptive field that changes across time, a crucial property to encode motion. Completion of this aim will enlighten us as to whether how the retina encodes motion can be fully explained by the efficient coding hypothesis.