# Neural Encoding in Balanced Networks Data-Driven Exploration

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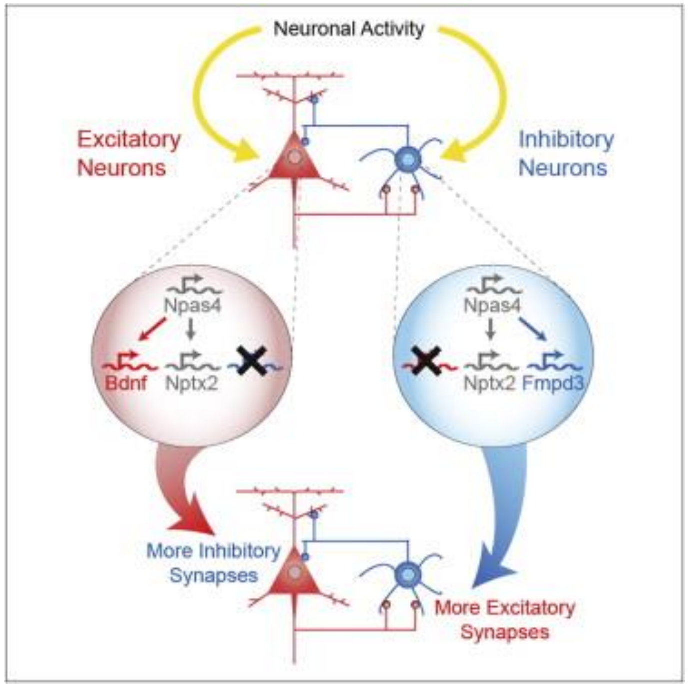
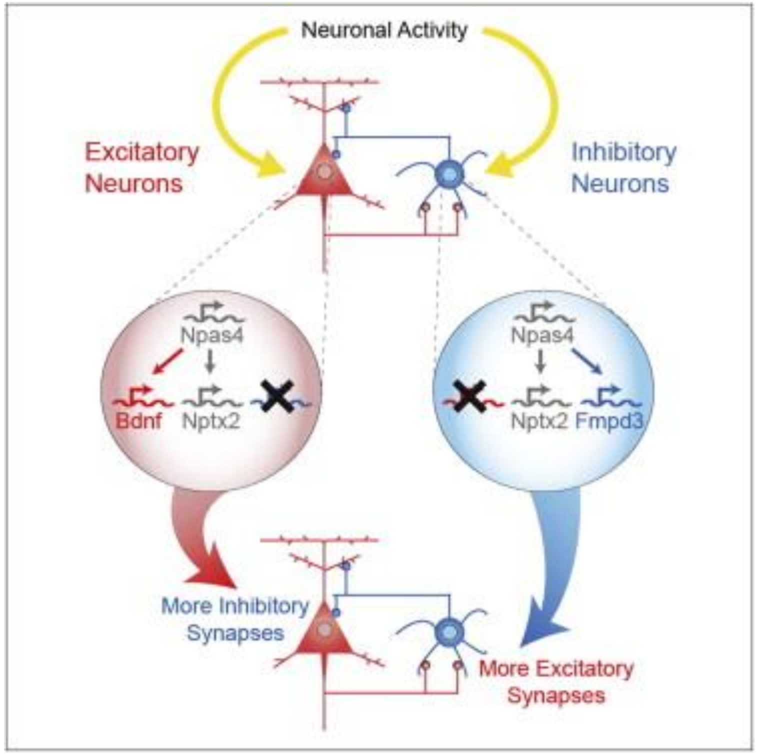
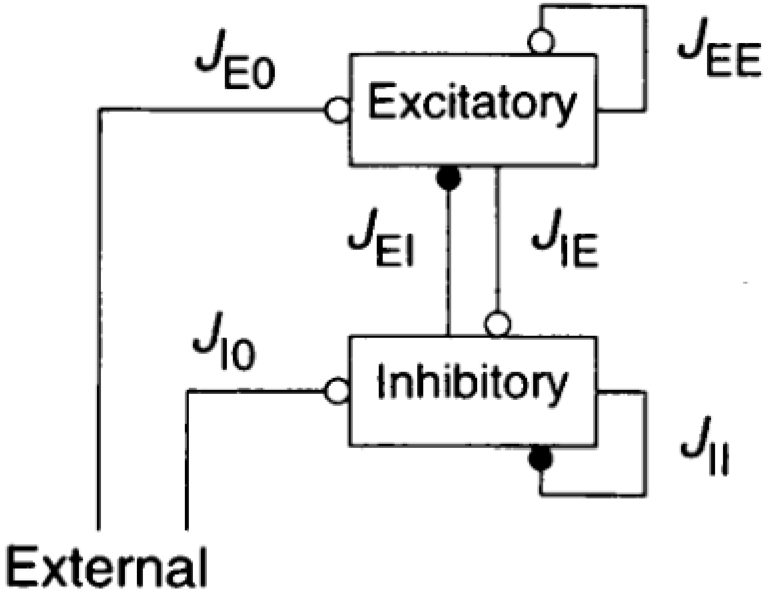


# Background: Excitatory and Inhibitory Neurons



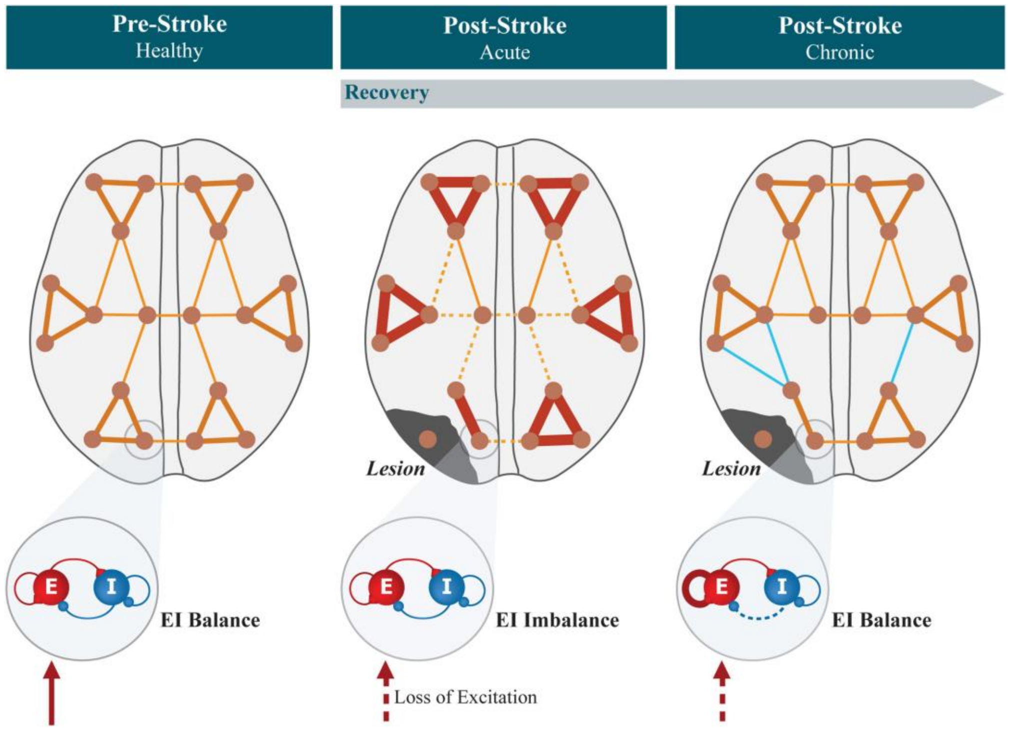

Neurons come in two main "flavors," **excitatory** and **inhibitory**. When an **excitatory** neuron receives enough input from other excitatory neurons, it **fires**, passing that signal along its axon to partners downstream. **Inhibitory** neurons usually tell other neurons **not to fire**. They are less plentiful than excitatory neurons but more diverse. In some ways, they are the real brains of the system, the machines in the background that pace and coordinate a ceaseless hum of electrical activity (I Spiegel,. 2014).

# Motivation: E/I Balance

In the context of neurophysiology, **balance of excitation and inhibition (E/I balance)** refers to the relative contributions of excitatory and inhibitory synaptic inputs corresponding to some neuronal event, such as oscillation or response evoked by sensory stimulation. In general, excitatory and inhibitory inputs of a neuron are said to be balanced if across a range of conditions of interest **the ratio between the two inputs is constant** (Michael Okun,. 2009). Without narrow control over the E/I ratio, runaway excitation or quiescence would occur, impeding adequate **information processing**. In clinical terms, disruption of E/I balance has become a dominant theory on the pathogenesis of various neurodevelopmental disorders (H Bruining,. 2020).

Hypothesis

Biological neural networks may possess superior encoding capabilities when operating in a balanced state.

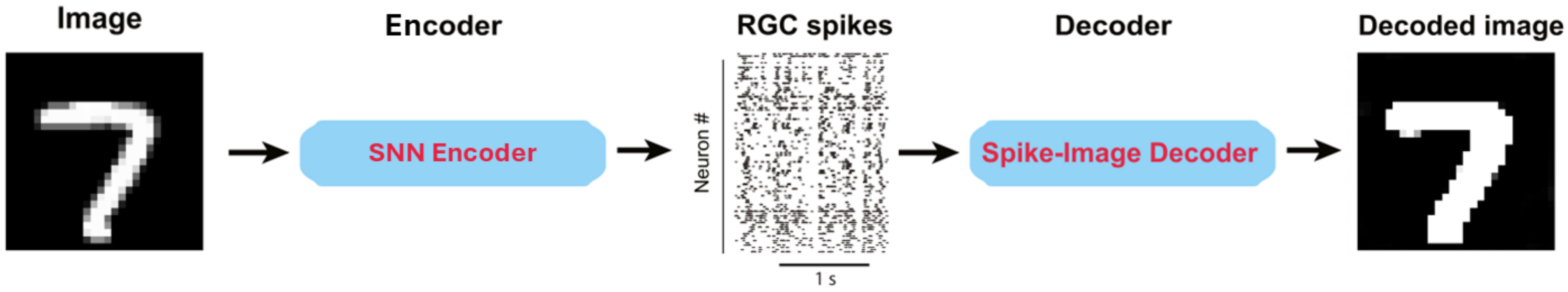



The evolution of connectivity and local EI balance in cortical networks after stroke. In the **healthy** brain, excitatory and inhibitory synapses are regulated locally by EI homeostasis so that **balance** is maintained. Focal lesions experienced by stroke patients lead to neural tissue necrosis in confined areas. In the **acute period** after lesion, areas that previously received white matter projections from the lesioned region experience a sudden reduction in the levels of external excitation, causing a local **imbalance** in excitatory and inhibitory activity. During the process of **recovery**, synaptic plasticity compensates for the reduced excitation by increasing/decreasing the strength of excitatory/inhibitory synapses unto pyramidal neurons, increasing their excitability to restore local EI **balance** (F Páscoa dos Santos,. 2022).

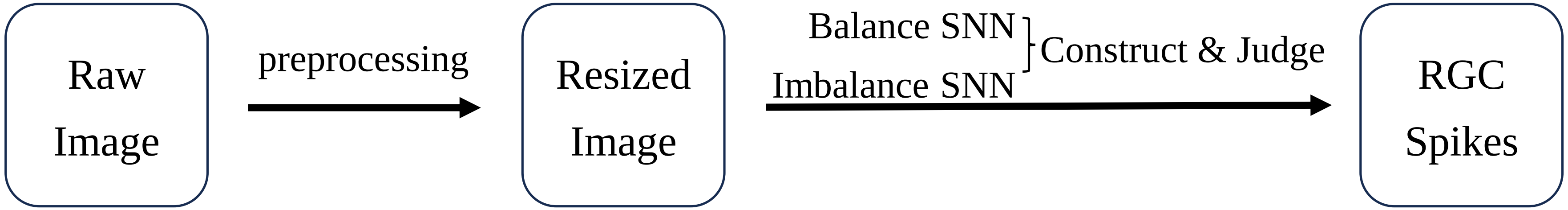
# Framework: Encoder and Decoder

**Hypothesis**: Biological neural networks may possess superior encoding capabilities when operating in a balanced state.

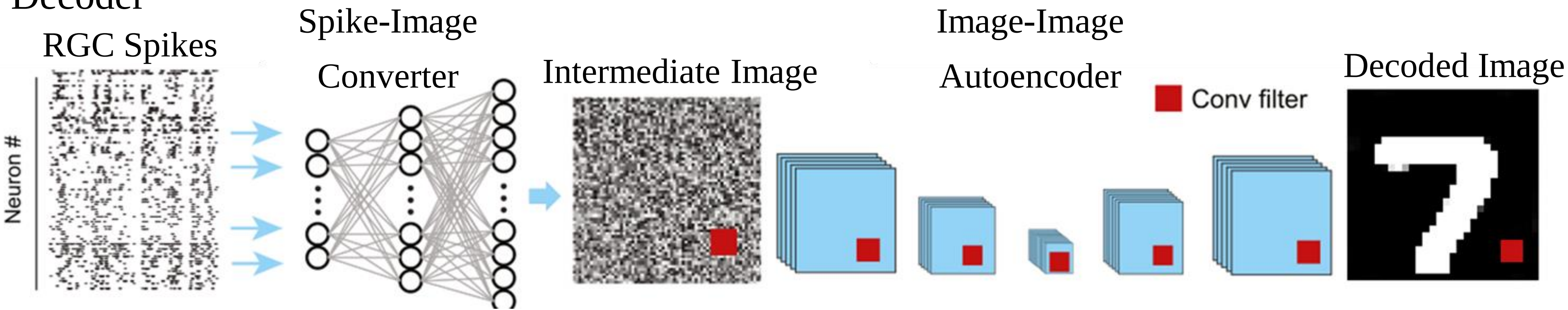
The hypothesis currently lacks empirical validation. To bridge this gap, our project takes a data-driven approach, employing machine learning techniques to explore neural encoding in balanced and non-balanced states.



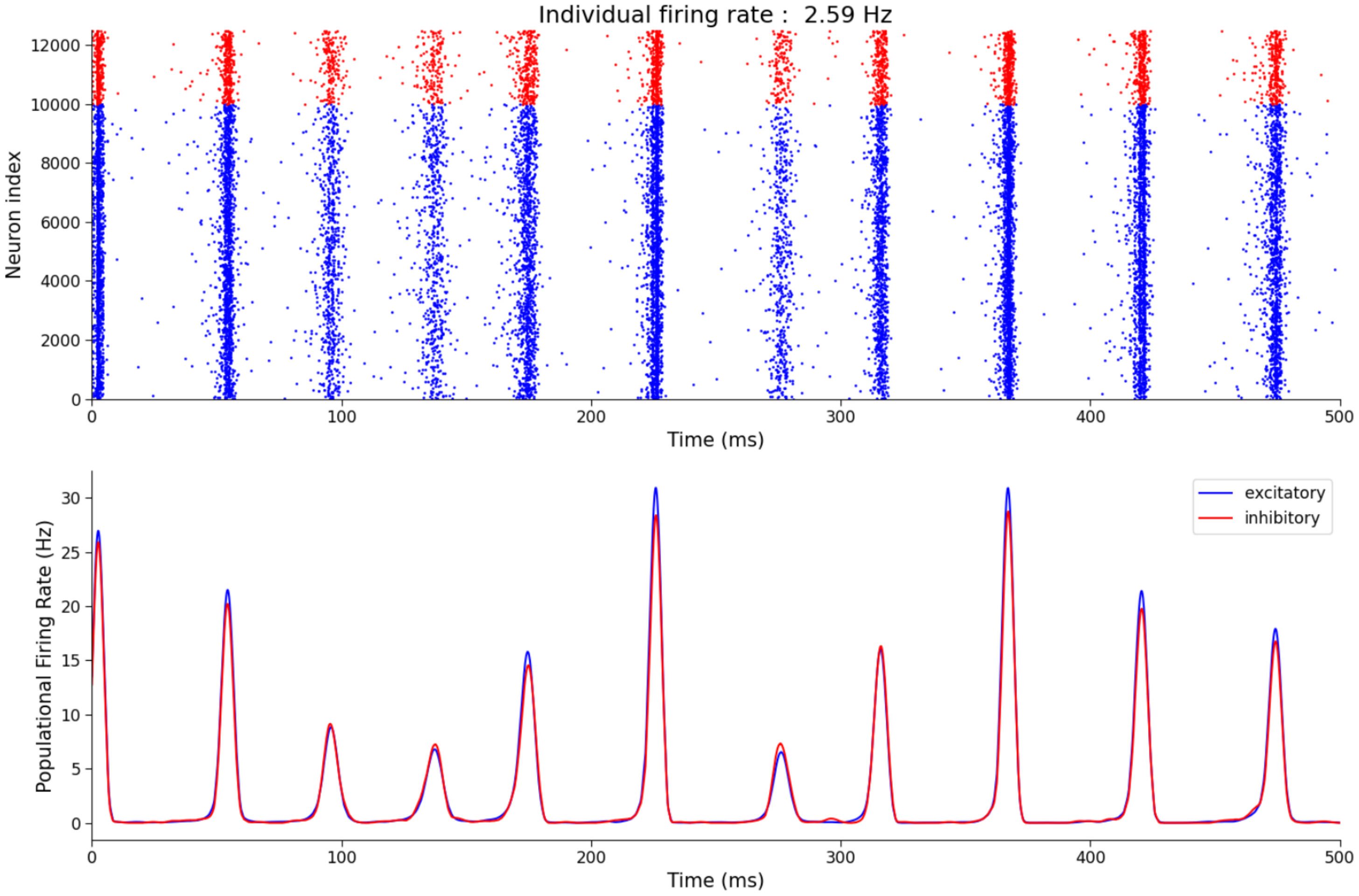

SNN Encoder




Spike-Image Decoder



# Guidance: Contructing and Judging E/I Balance



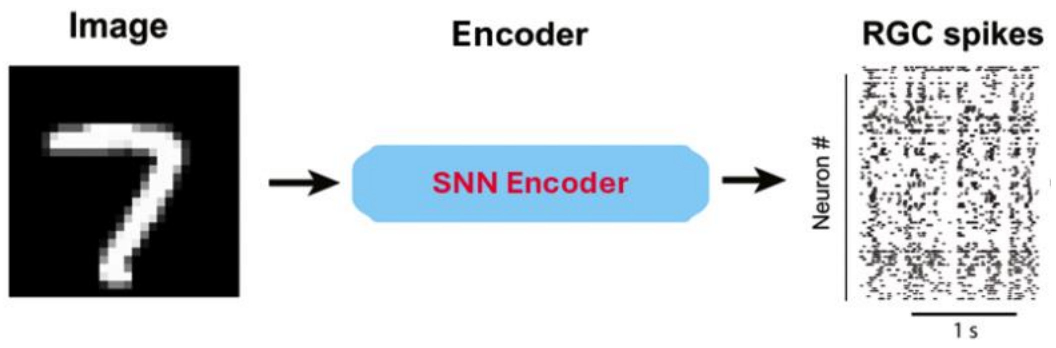

## Initialization

- Excitatory and inhibitory synaptic currents of cortical neurons are approximately **balanced in strength** when E/I balance (Shadlen and Newsome, 1994, 1998).
- When **inhibition** is blocked pharmacologically, cortical activity becomes epileptic (Dichter and Ayala, 1987), and neurons may lose their selectivity to different stimulus features (Sillito, 1975).
- E/I balance emerges naturally if the network is **sparsely connected** (van Vreeswijk and Sompolinsky, 1996; Vogels et al., 2005).

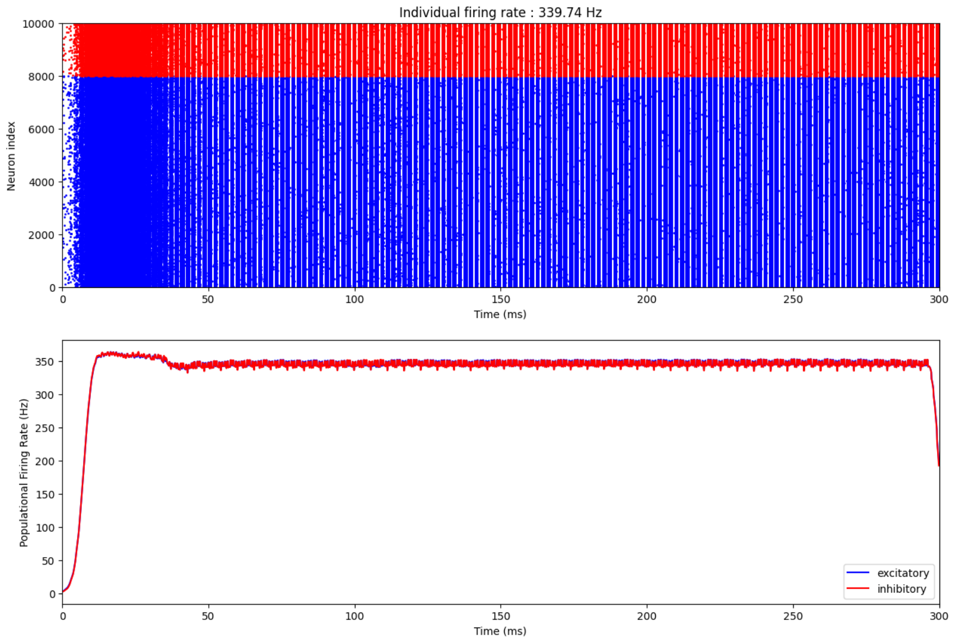
## Relation between external input and output

- The population-averaged rates increase nearly **linearly** with the external input when E/I balance (C van Vreeswijk., 1996).
- The balanced network **quickly** tracks changes in the rate of the external input (C van Vreeswijk., 1996).

# 2.Encode image by SNN

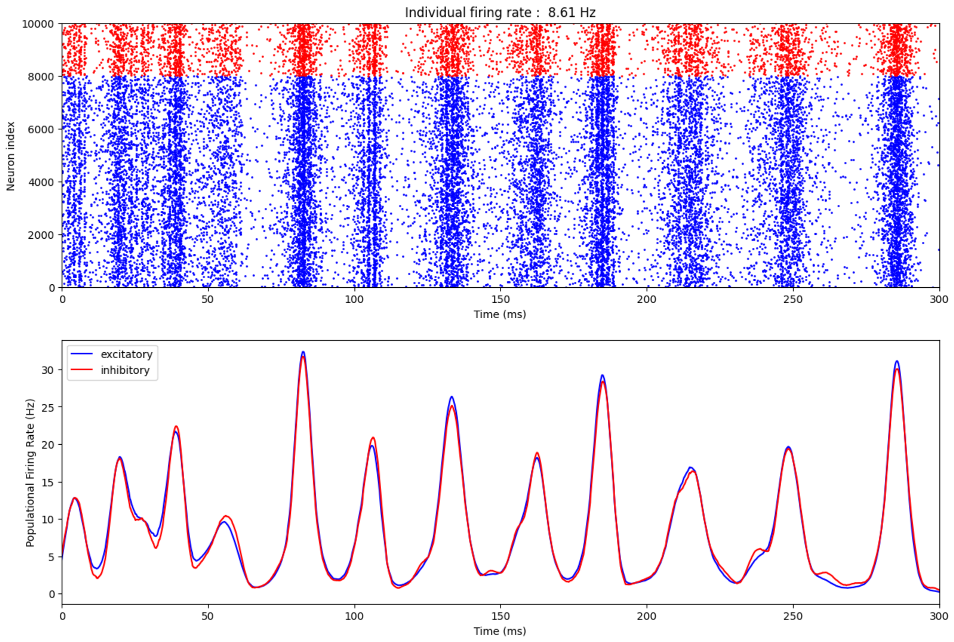


# Imbalance and balance




Unbalanced state

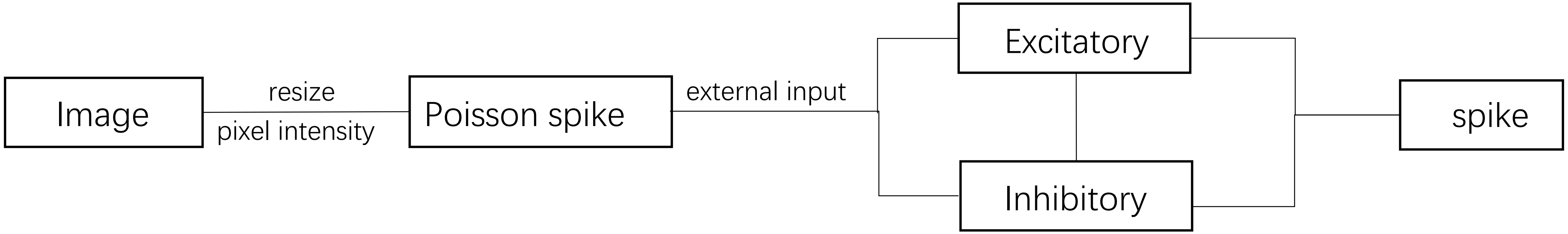
$$g = \frac{\text{Inhibitory input}}{\text{excitatory input}} = 3.5 \quad \text{regular spike}$$

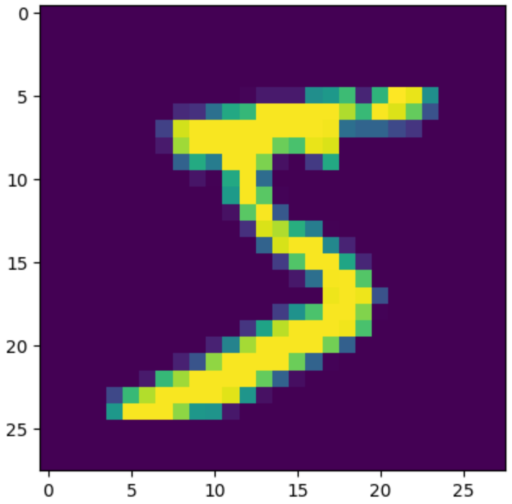


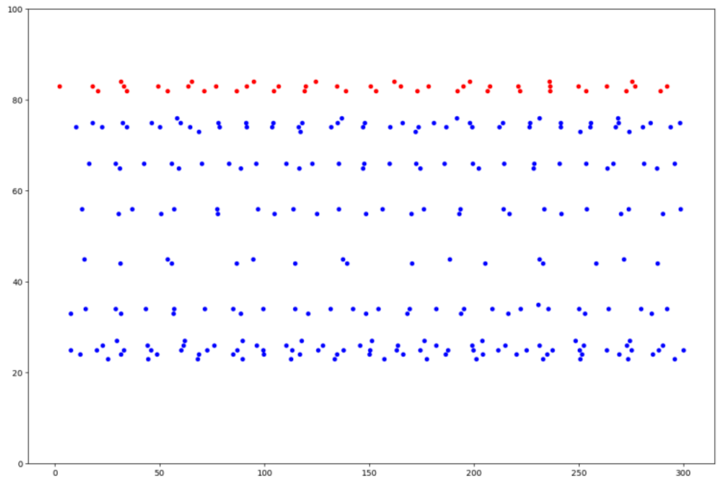

Balanced state

$$g = \frac{\text{Inhibitory input}}{\text{excitatory input}} = 5 \quad \text{irregular spike}$$

# Structure of SNN



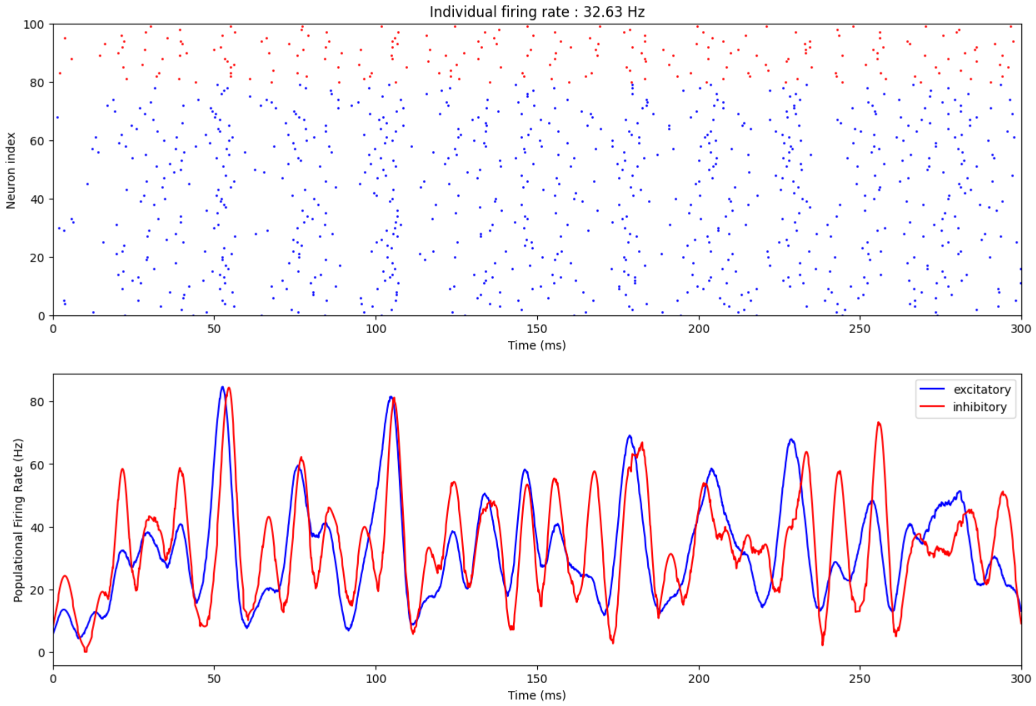



Spike of 100 neurons

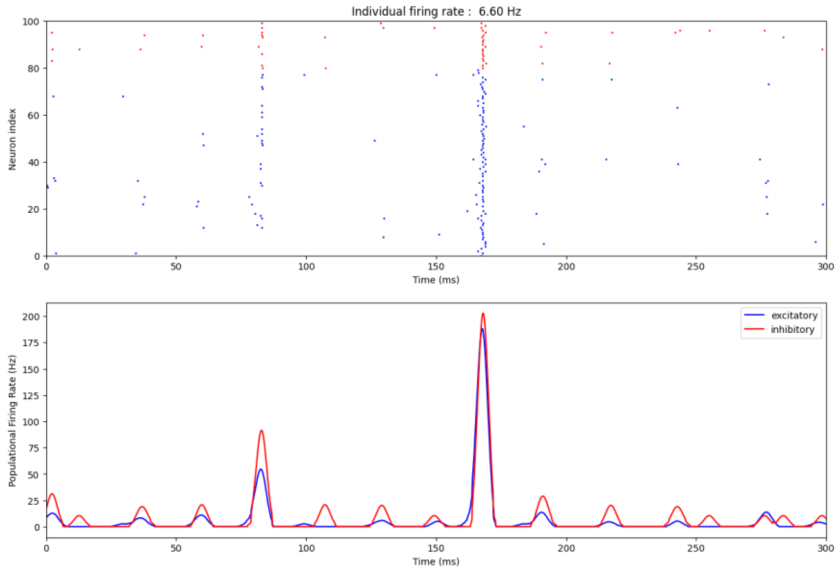
# Imbalance and balance

Parameter: g, connectivity probability, threshold potential

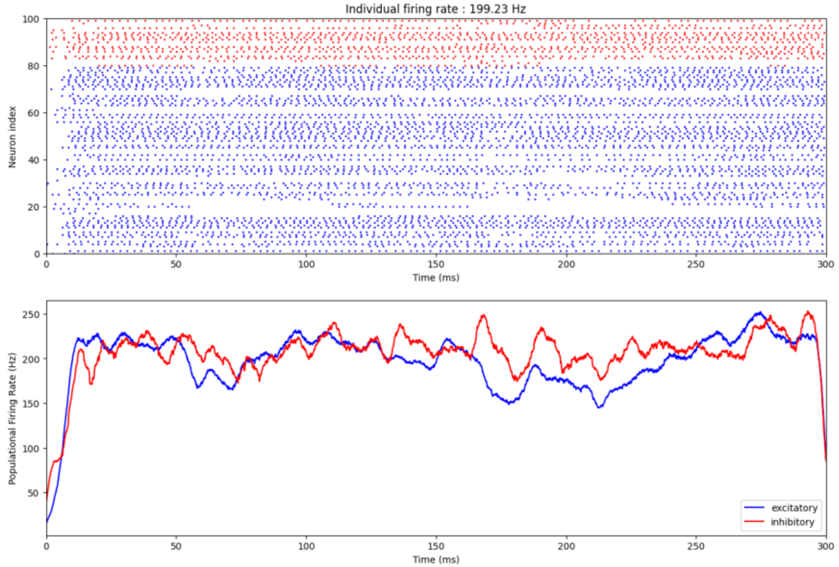
g does not influence the balance?




Balanced state



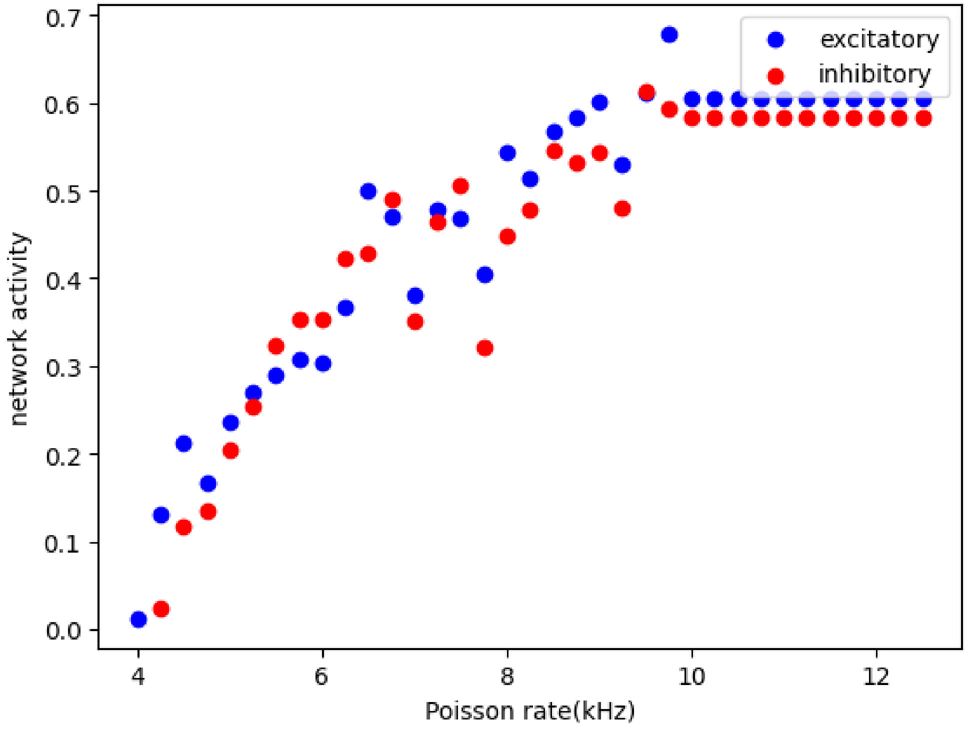

Unbalanced state 1



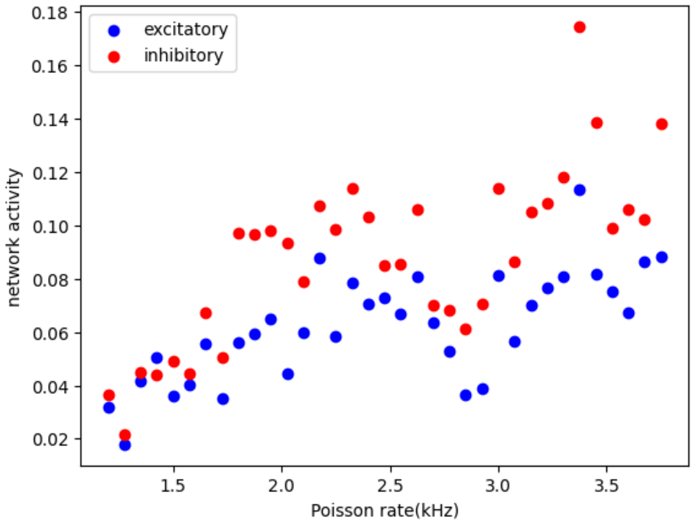

Unbalanced state 2

# linearity between external input and network activity

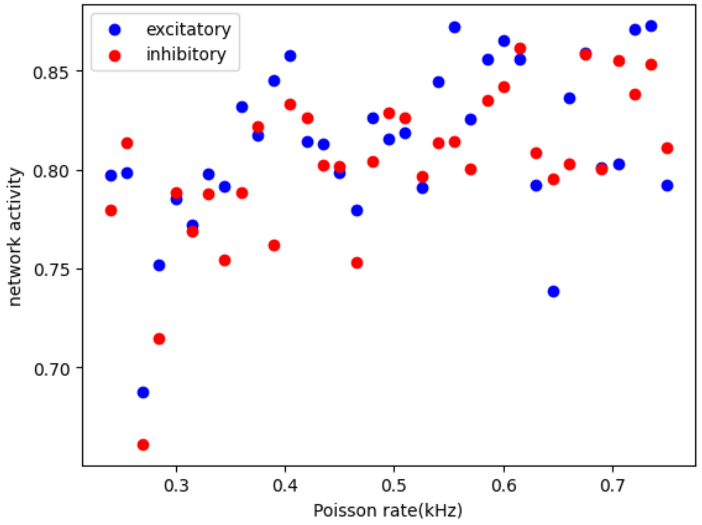
Network activity is firing rate divided by maximum rate




Balanced state

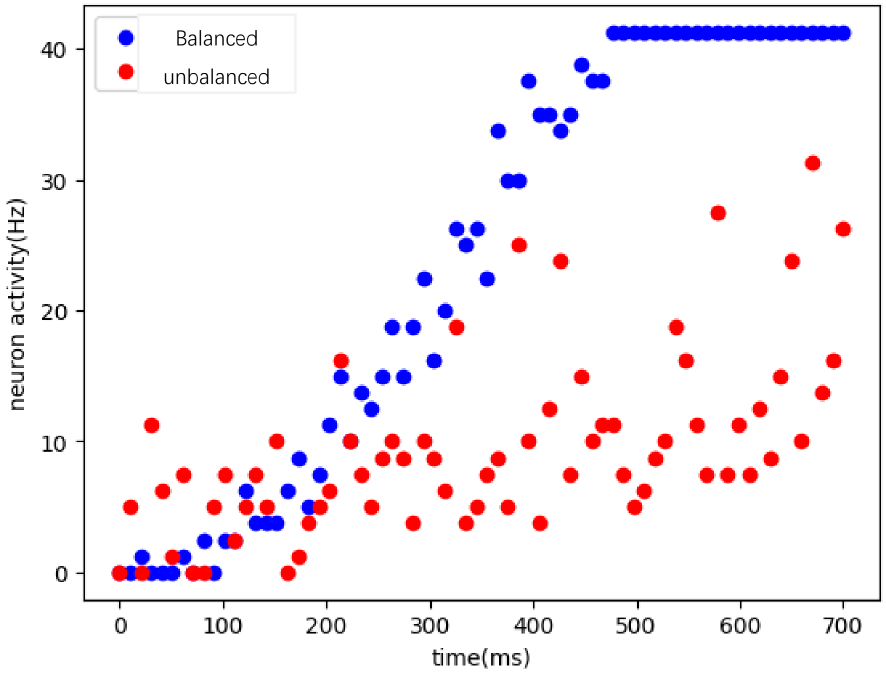



Unbalanced state 1




Unbalanced state 2

# Response to the external input




External input increases from t=0ms to t=700ms linearly

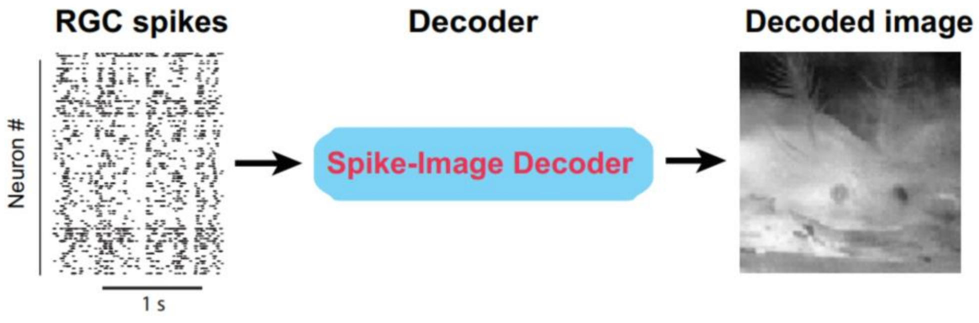
The balanced network tracks the external rate quickly and accurately, while the unbalanced network does not perform well see code&data on：

https://jbox.sjtu.edu.cn/l/X1pSff

# 3. Introduction to the spikes-to-image decoder models

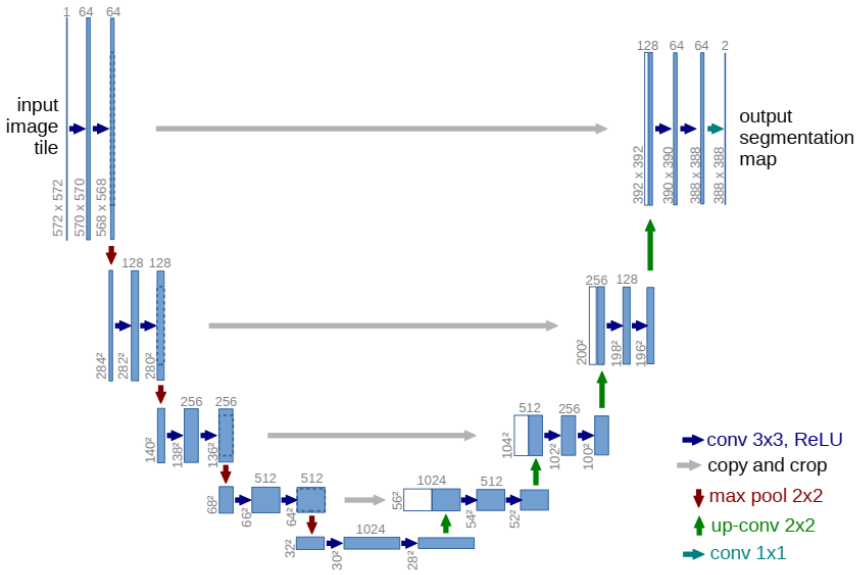
---MLP(3-layer fully connected NN)+Unet

---MLP+VAE(Variational Autoencoder)

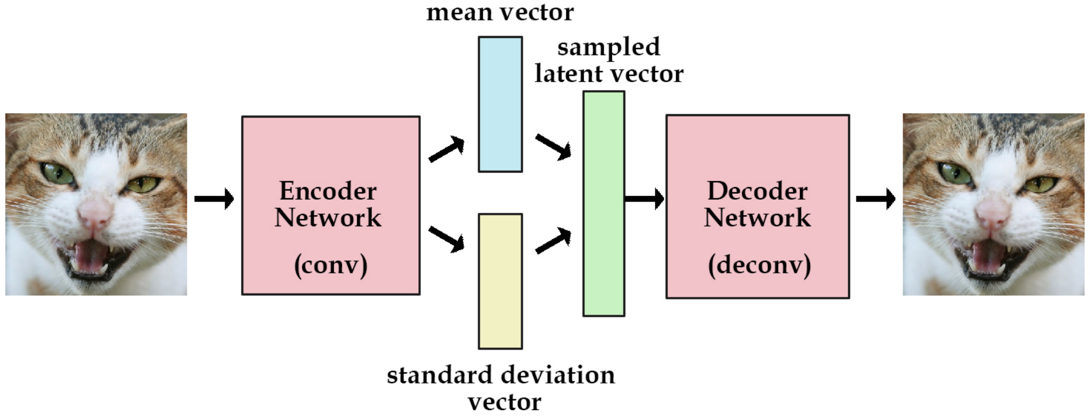


# Model1: U-Net

The network consists of a contracting path and an expansive path, which gives it the u-shaped architecture. The contracting path is a typical convolutional network that consists of repeated application of convolutions, each followed by a ReLU and a max pooling operation. During the contraction, the spatial information is reduced while feature information is increased. Then there are a large number of feature channels in the upsampling part, which allow the network to propagate context information to higher resolution layers. As a consequence, the expansive path is more or less symmetric to the contracting part, and yields a u-shaped



# 2.Variational Autoencoder

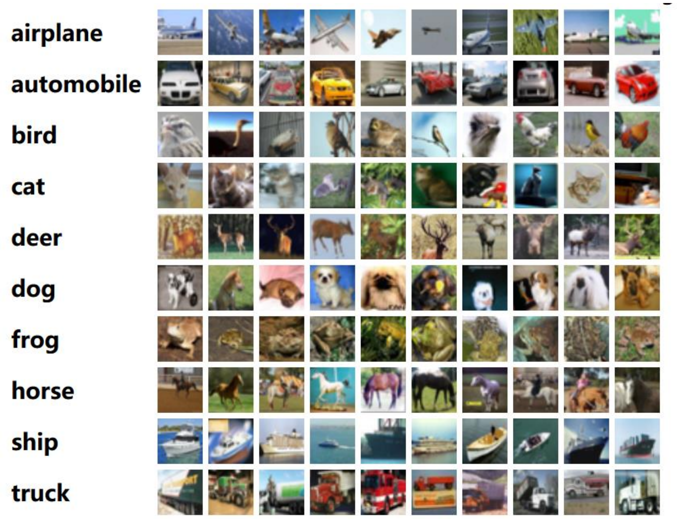



- VAE's advantages over ordinary autoencoders gained by adding a constraint on the encoding network, that forces it to generate latent vectors that roughly follow a unit gaussian distribution.
- So in general, the loss function consists of two parts---MSE between generated images and real images+ KL divergence that measures how closely the latent variables match a unit gaussian. This is a tradeoff between accuracy and robustness that could enhance the model's denoising capabilities/robustness to the noises.
- $$D_{\mathrm{KL}}(P\|Q)=\sum_{x\in\mathcal{X}}P(x)\log\left(\frac{P(x)}{Q(x)}\right)$$ relative entropy of one random variable wrt another:

# 4. Images Reconstruction Results

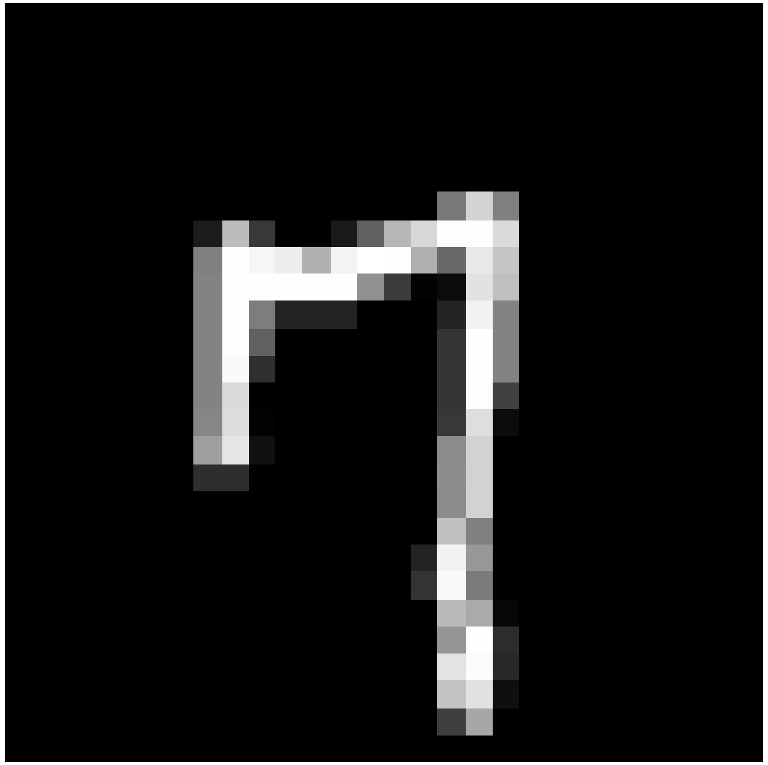
---MNIST

---CIFAR-10

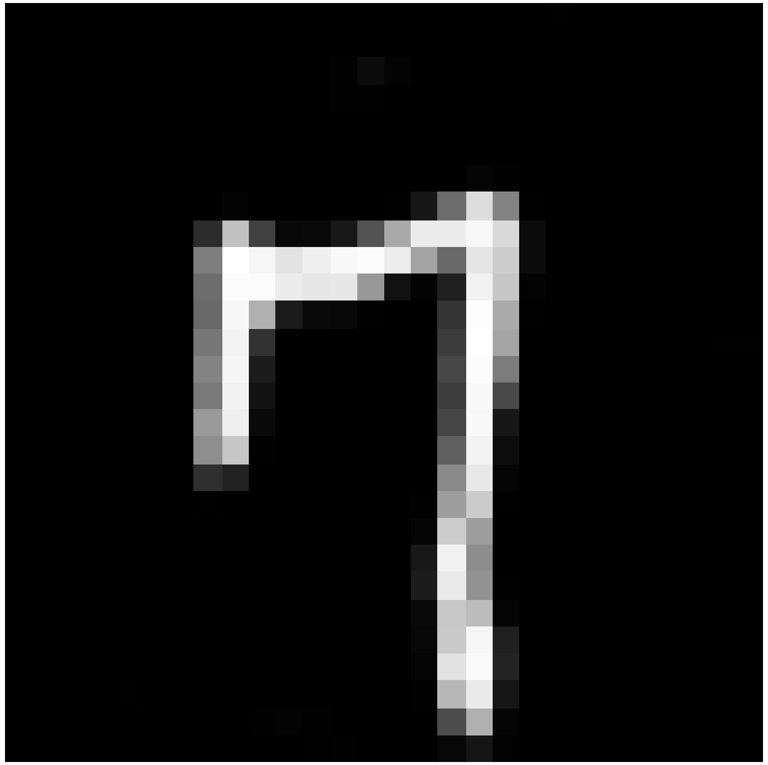


# MNIST by SNN(balance)-MLP-Unet

## original image



## renconstructed image

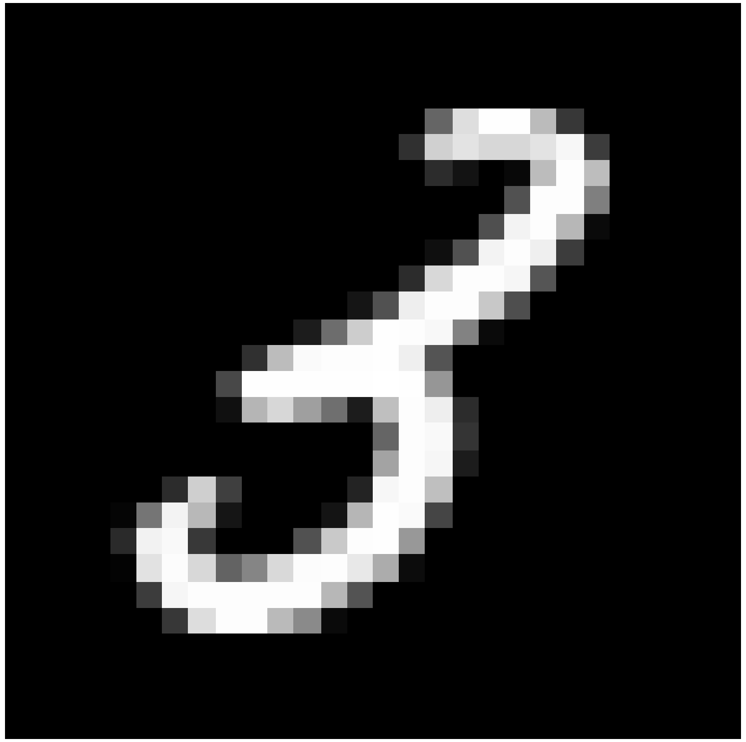


PSNR：31.251113891601562

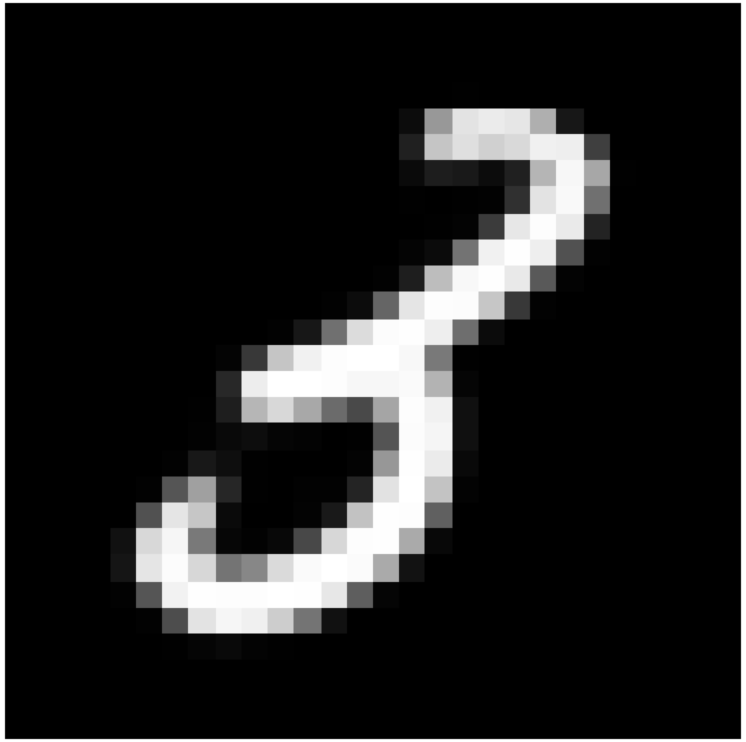
SSIM: 0.98386505302453

# MNIST by SNN(imbalance)-MLP-Unet

## original image



## renconstructed image

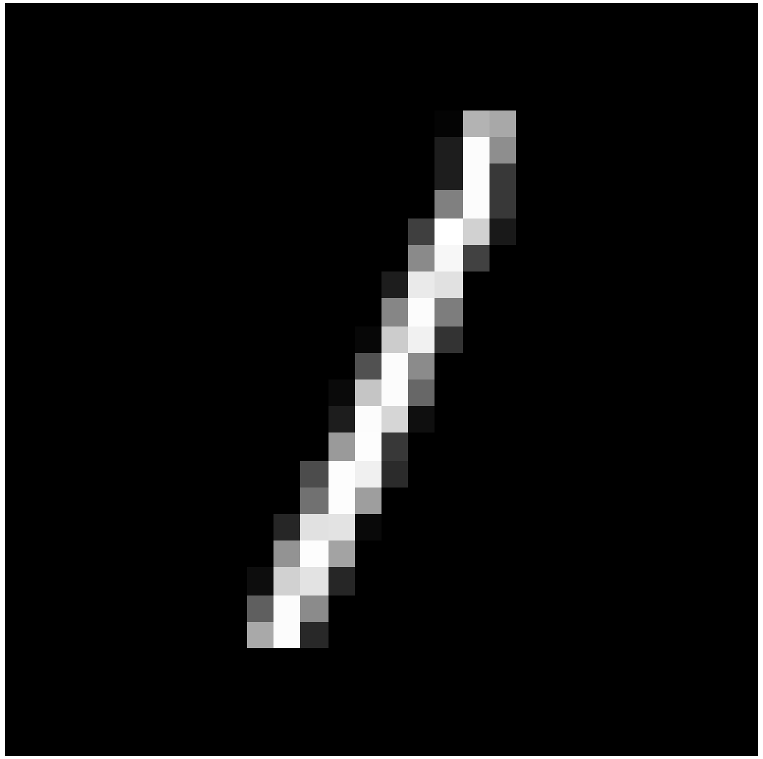


PSNR：30.19415283203125

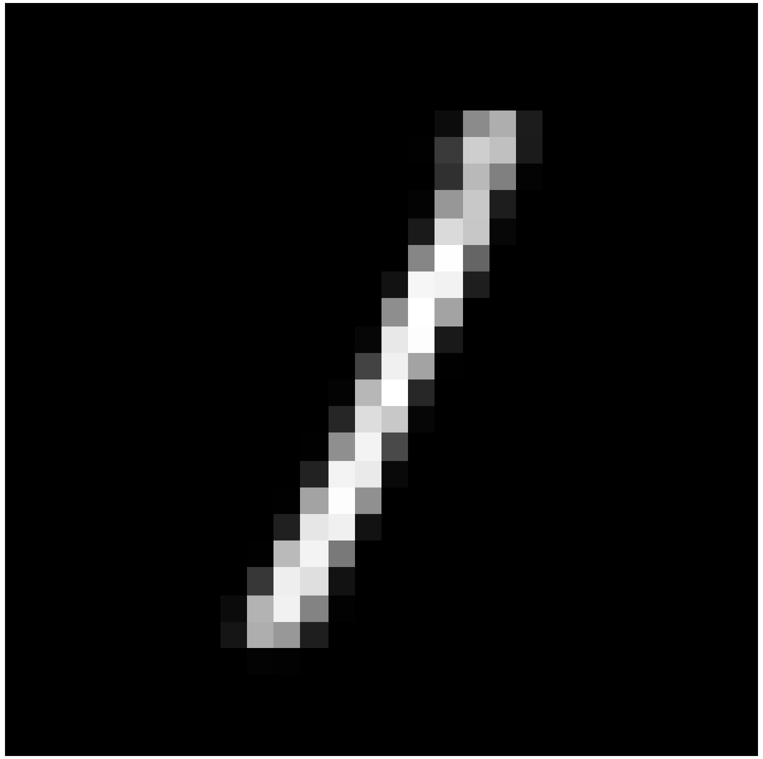
SSIM: 0.9859449456576969

# MNIST by SNN(balance)-MLP-VAE

## original image



## renconstructed image

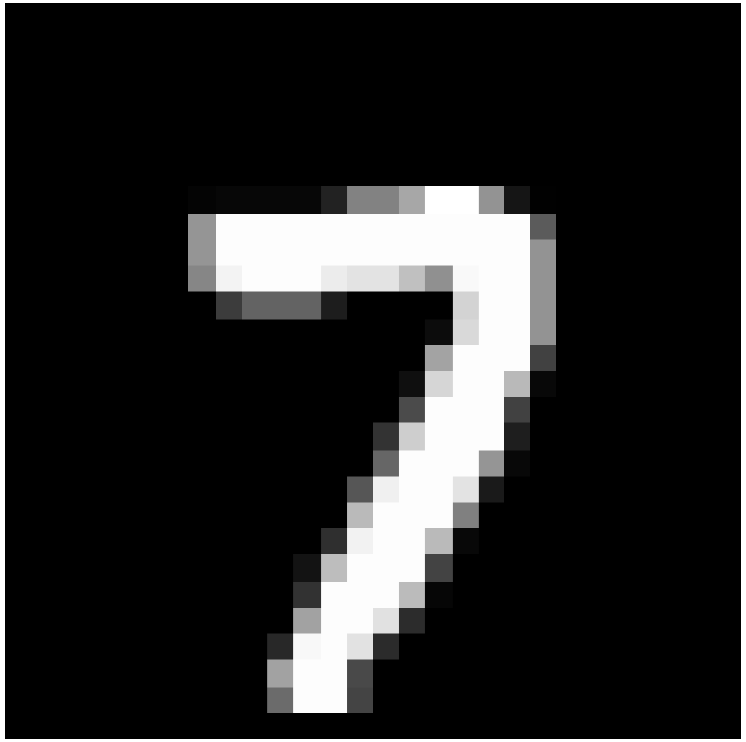


PSNR：28.366497039794922

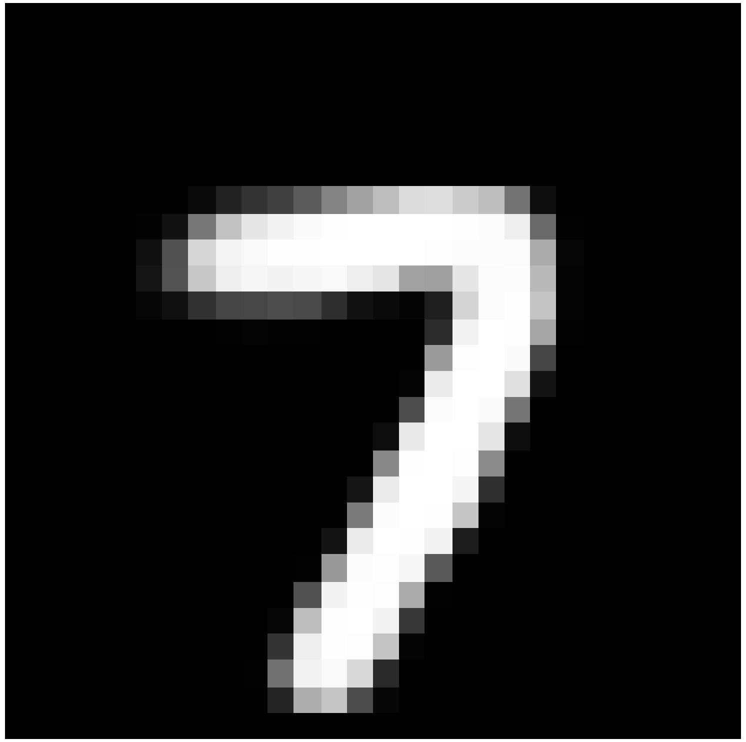
SSIM：0.9687115528245319

# MNIST by SNN(imbalance)-MLP-VAE

## original image



## renconstructed image



PSNR：　24.432823181152344

SSIM：0.9378018503427755

# CIFAR-10 by SNN(balance)-MLP-Unet

**original image**

**renconstructed image**

PSNR： 24.460479736328125

# CIFAR-10 by SNN(imbalance)-MLP-Unet

**original image**

**renconstructed image**

PSNR：21.56488609313965

# Reconstruction Quality : Balance SNN versus Imbalance SNN (Accuracy)

**mean, median and range of psnr/ssim in a batch ( balance )**

- MNIST (mean, median, range)

--Unet: psnr:29.6532 , 29.4535 , (26.92 , 32.06)

ssim:0.9835 , 0.9848 , (0.9779, 0.9889)

--VAE: psnr : 21.0218 , 19.9632 , (18.89, 28.37)

ssim : 0.8856 , 0.88067141 , (0.8042, 0.9687)

- CIFAR-10 (mean, median, range)

psnr : 19.0059 , 18.7384 , (16.73, 24.46)

**mean, median and range of psnr/ssim in a batch ( imbalance )**

- MNIST (mean, median, range)

--Unet: psnr:28.7320 , 29.2134 , (26.13, 32.00)

ssim:0.9822 , 0.9843 , (0.9718, 0.9886)

--VAE: psnr:20.9874 , 18.8574 , (15.88, 29.07)

ssim:0.8777 , 0.8702 , (0.7755, 0.9836)

- CIFAR-10 (mean, median, range)

psnr : 18.0818 , 17.4775, (15.50, 21.56)

# Reconstruction Quality : Balance SNN versus Imbalance SNN (Generalizability)

**performance on the test set （balance） (average loss)**

- MNIST

--Unet: 0.0105

--VAE: 0.0364

- CIFAR-10 ：

--Unet: 0.0212021728977561

**performance on the test set （imbalance） (average loss)**

- MNIST

--Unet: 0.0186

--VAE: 0.0227

- CIFAR-10 ：

--Unet: 0.0363

# Discussions

- The generate/learning ability of CNN models

Does this make the differences of the input data from the balance/imbalance spikes trivial?

- Methods to process RGB images

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