Spiking Neural Networks (SNN)

Pros
- sparse nature of spike events
- event-driven
- low-powered

Cons:
- hard to train
  - complex dynamics of neurons
  - non-differentiable spike operatio
- information loss (under/over-activation problem)

SNN: mimic how information is encoded and processed in the human brain by employing spiking neurons as computation units.

与DNN区别:

transmit info
- (DNN) a real value (continuous)
- (SNN) precise timing (temporal) of spike trains consisting of a series of spikes (discrete)

Spike trains → a series of spikes to convey information between neurons

"Temporal Aspects in Information Transmission"

Event-driven Computation: the spiking neurons integrate inputs into a membrane potential when spikes are received and generate (fire) spikes when the membrane potential reaches a certain threshold.

膜电位

DNN-to-SNN :

$$\text{DNN} \xrightarrow[\text{pre-trained parameters}]{\text{import}} \text{SNN}$$

input z

membrane potential V_{mean}

threshold voltage

$$V_{mean,j}^{l}(t) = V_{mean,j}^{l}(t-1) + z_j^{l}(t) - V_{th}\,\Theta_j^{l}(t)$$

integrated value

input of j^{th} neuron

Spike

in the lth layer

unit step function

$$\Theta_i^l(t) = U(V_{mean,i}^l(t) - V_{th})$$

$$Z_j^l(t) = \sum_i W_{i,j}^l \, \Theta_i^{l-1}(t) + b_j^l$$

Firing rate: $\frac{N}{T}$

N: total number of spikes

T: given time step T

Layer Norm:

$$\tilde{W}^l = W^l \frac{\lambda^{l-1}}{\lambda^l}$$

$$\tilde{b}^l = \frac{b^l}{\lambda^l}$$

λ : maximum activations calculated from
the training set (in layer ℓ)