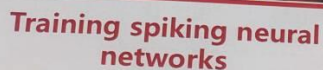


2023 8.29 PM
Day - 07



王超名
chao.brain@qq.com



01

Introduction

Q & A:

神经元的 bursting 12 GHz 控制

计算精度? 计算精度!

Q GIF 和 LIF 区别?

为什么 GIF 可以训练好 LIF 就不行

有些 burst 节律与皮层同步化之类
在觉醒和注意力之类的发挥作用。

目录 CONTENTS



- 01 Introduction
- 02 Trainable Neuron Models
- 03 Neural Coding
- 04 Training a SNN network for classifying MNIST
- 05 Training a GIF network for working memory

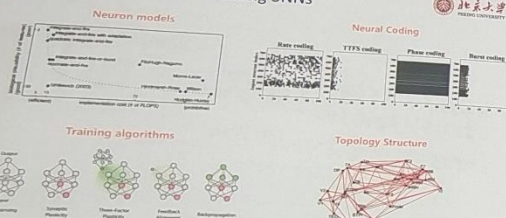


So why should I care about SNNs?

- **Neuroscience**
 - SNNs are what the brain does. If we want to fully understand the brain we need to understand SNNs.
- **Intelligence**
 - They're the basis of the only known system for general intelligence.
- **Intellectual challenge**
 - Find a way to think about hybrid continuous / discrete system, and computation based on this
- **The coming revolution**
 - Exciting times for SNNs with new ways to train them (will talk about it in second half)
- **Neuromorphic hardware**
 - Low power consumption.
- **Advantages of computation with SNNs?**
 - Fast computation / rapid decision-making
 - Multiplexing



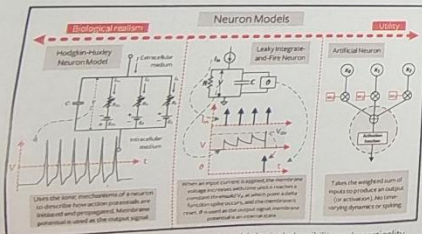
Basic Elements of Training SNNs



02

Trainable Neuron Models

The spectrum of neuron models



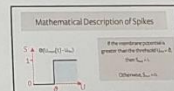
The LIF neuron sits in the sweet spot between biological plausibility and practicality

Non-differentiable problem

- The discharge process is a **non-differentiable** process

$$s(t) = \theta(U_{mem}(t) - U_{thr})$$
- $\theta(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$ is a **Heaviside step function**
- The derivative of the Heaviside function $\theta(x)$ is the **Delta function**

$$\delta(x) = \begin{cases} +\infty, & x = 0 \\ 0, & x \neq 0 \end{cases}$$
- Unable to use $\delta(x)$ to calculate during **backpropagation**



$$\frac{\partial L}{\partial W} = \frac{\partial L}{\partial S} \frac{\partial S}{\partial U} \frac{\partial U}{\partial I} \frac{\partial I}{\partial W}$$
 链式法则
 (S,U) → spike 神经网络
 This is the problem!

This is the problem:

Surrogate gradient learning

前向: Heaviside
反向: surrogate function 即 sigmoid.

替代 Heaviside
Sigmoid 函数
(类似 Heaviside)

The forward function

$$g(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

The surrogate function

$$g(x) = \text{sigmoid}(ax) = \frac{1}{1 + e^{-ax}}$$

The surrogate gradient

$$g'(x) = a \cdot (1 - \text{sigmoid}(ax)) \cdot \text{sigmoid}(ax)$$

Available surrogate gradient functions

Define a function by instantiating a class
`fun = nn.SurrogateSigmoid(alpha=1.0)`
`b = fun(a)`

Use the surrogate function directly
`b = nn.SurrogateSigmoid(a, alpha=1.0)`

Although wrong, they work

■ All kinds of surrogate gradient functions are equally good
 ■ Different surrogate gradient functions have varying sensitivity to hyperparameters

打通: work 好

03 Neural Coding

怎样将外界刺激输入成 spike?

Why do we take care of neural coding?

Spikes, Sparsity and Static-Suppression

- Spikes
- Sparsity
- Static-Suppression (event-driven processing)

Spiking encoding

Convert the input into a spike train of sequence.

Neural encoding methods

Rate Coding: $B(t) = p(t) \cdot t$

Latency Coding: Each feature corresponds to a single spike. The latency of the feature determines how fast the spike occurs. On spikes + off spikes.

Delta Modulation: Input Data, On spikes, On spikes + off spikes.

Rate (Poisson) coding

Problems of rate coding:

- The cortex globally encodes information as spike rates.
- Rate-coding can only explain, at most, the activity of 15% of neurons in the primary visual cortex (V1).
- Reaction Response Times. We know that the reaction time of a human is roughly around 250 ms. If the average firing rate of a neuron in the human brain is on the order of 10Hz, then we can only process about 2 spikes within our reaction timescale.

brainpy.encoding.PoissonEncoder(gain, first_spk_time)

每个动作 fire rate

Latency (time-to-first spike) coding

小于 V_{thr} 无 spike
大于 V_{thr} 有 spike

Input pixel (P) Time-to-first spike coding

Latency Coding: "linear=True"

Spike times are clamped at a maximum of the threshold V_{thr} .

Latency Coding: The RC Model

Capacitor charging equation: $C \frac{dV}{dt} = I - V/R$

Capacitor voltage: $V(t) = V_{thr} (1 - e^{-t/\tau})$

Time to first spike: $t_s = -\tau \ln(1 - V_{thr}/I)$

Latency (time-to-first spike) coding

brainpy encoding: `LatencyEncoder(method='linear/log')`

rate coding as: 按 poisson 分布的随机性
改变有但具有鲁棒性

Delta modulation

Dynamic Vision Sensor (DVS)

This silicon retina only sees motion

Input Data

Delta Modulation

A small change may induce a large positive or negative swing in the output, generating on or off spikes.

On spikes = off spikes

04

Training a SNN network for classifying MNIST

写个下, 会训练神经网络
这神经网络向在 yastoy 图行指定跟踪
数据不一致, 根据数据来
调整模型输入刺激权重

Is spiking neural networks trainable?

监督学习

Unsupervised learning

Supervised learning

Surrogate gradient methods

A LIF based SNN network model

Output layer

Recurrent layer

Input layer

Continuous Version

$$\tau_i \frac{dI}{dt} = -I + W \sum_j d(t - t_j)$$

$$\tau_v \frac{dV}{dt} = -V + V_{rest} + RI$$

Discrete Version

$$I(t + \Delta t) = -\alpha I(t) + W \sum_j d(t - t_j) + I_{rest}$$

$$V(t + \Delta t) = -\alpha V(t) + V_{rest} + RI(t + \Delta t) \Delta t$$

$$dI/dt = \begin{cases} 1 & \text{if } V(t + \Delta t) > V_{thr} \\ 0 & \text{otherwise} \end{cases}$$

$$V(t + \Delta t) = V(t + \Delta t) - V_{thr} \Delta t + \Delta t$$

where $\alpha_I = e^{-\frac{\Delta t}{\tau_i}}$ and $\alpha_V = e^{-\frac{\Delta t}{\tau_v}}$

exp-Euler 积分

A recurrent representation of SNNs

building block

Recurrent representation of spiking neurons

Spiking neuron with implicit and explicit recurrence

Equivalent spiking neuron (illustrated with an unrolled computational graph (implicit recurrence is omitted))

Backprop through time

W1: 自身 spike 对自身连接
W2: 前 spike 对自身连接

Backprop through time

where $\alpha_I = e^{-\frac{\Delta t}{\tau_i}}$, and $\alpha_V = e^{-\frac{\Delta t}{\tau_v}}$

$$\frac{dE}{dW_1} = \sum_i \frac{dE}{dI_i} \frac{dI_i}{dW_1}$$

$$\frac{dE}{dW_2} = \sum_i \frac{dE}{dI_i} \frac{dI_i}{dW_2}$$