Recent Advancements in Spiking Neural Networks

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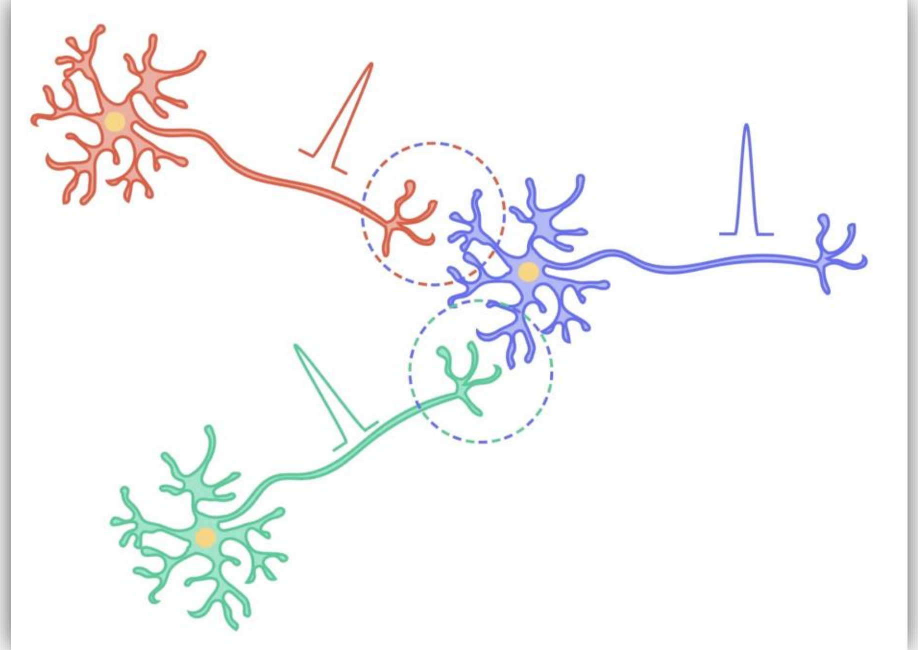
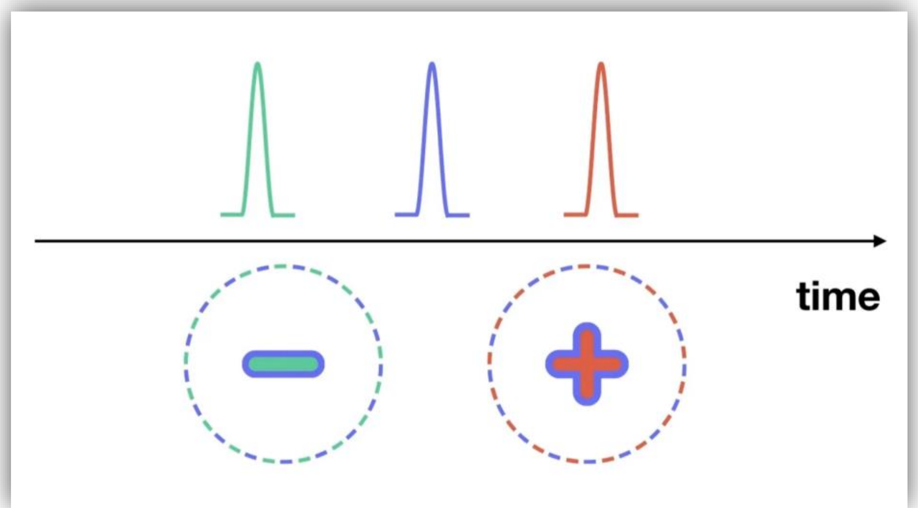
Content





Introduction

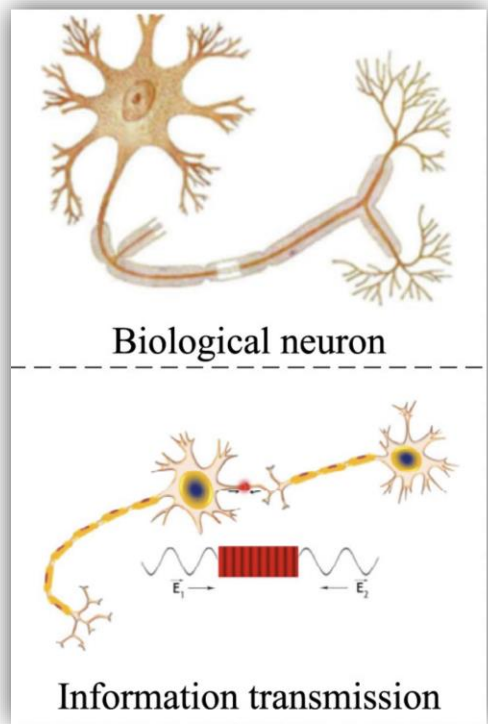
Spiking Neural Networks are often called the third generation of neural networks [2]. The main features of this architecture are the following:

- neural networks inspired by the human brain,
- energy efficient on specific hardware.

Context

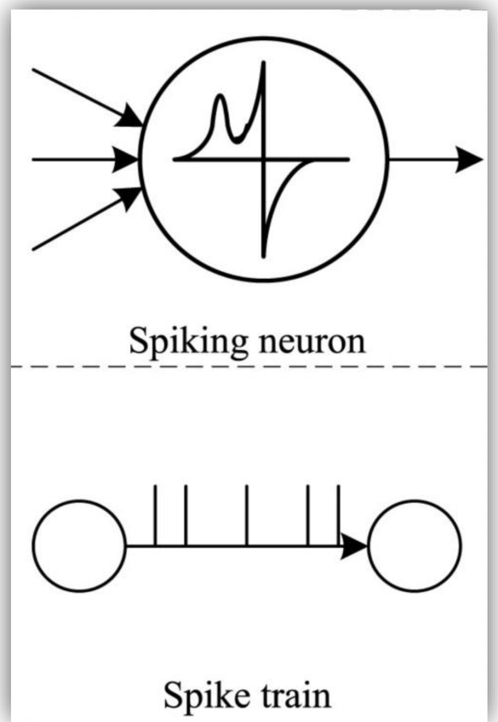
Biological Neural Network

[3]



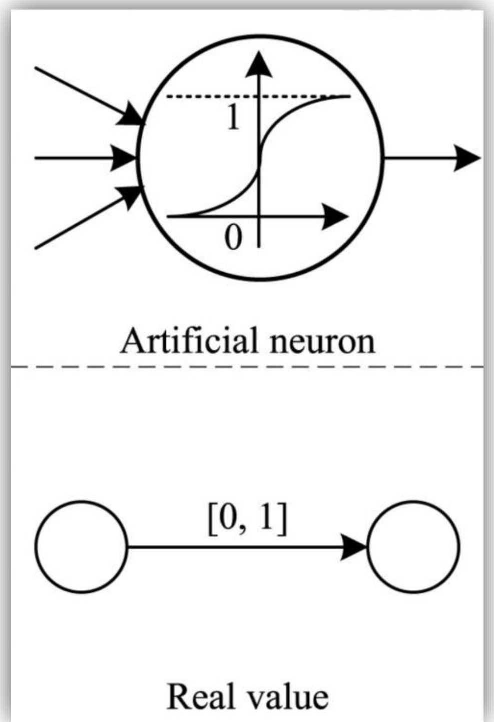
Spiking Neural Networks

[3]



Artificial Neural Network

[3]



Context

Biological Neural Network

- Information is transmitted through discrete electrochemical signals via synapses.
- Time plays a critical role; real neurons fire at specific moments based on ion-channel dynamics.

Spiking Neural Networks

- Information is transmitted through discrete spikes across synapses.
- Spike timing plays a key role (Temporal coding via spikes).

Artificial Neural Network

- Information is transmitted through continuous values passed between layers.
- No explicit notion of time; computations are synchronous.

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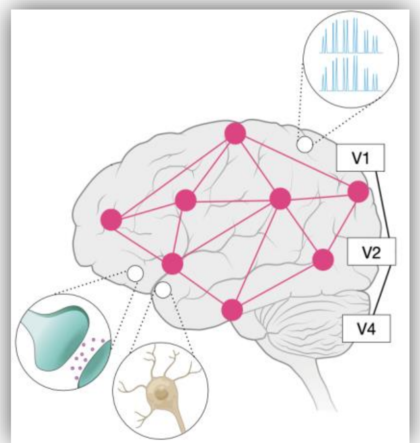

[1]

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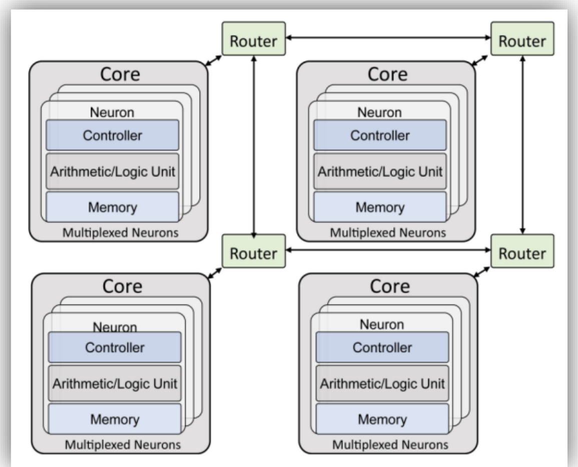

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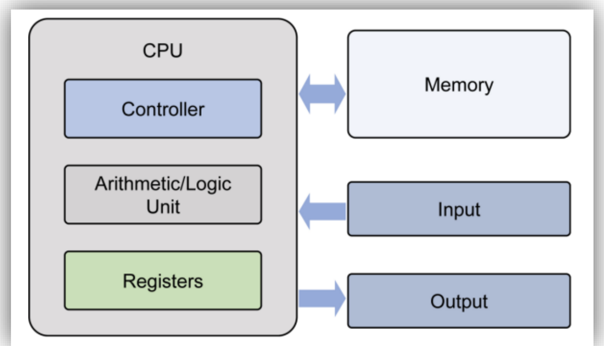


[4]

Context

Biological Neural Network

- Information is transmitted through discrete electrochemical signals via synapses.
- Time plays a critical role; real neurons fire at specific moments based on ion-channel dynamics.
- Very efficient; human brain consumes ~20 watts [1].
- Massively parallel at the neuron level.
- Asynchronous, sparse spiking activity.

Spiking Neural Networks

- Information is transmitted through discrete spikes across synapses.
- Spike timing plays a key role (Temporal coding via spikes).
- Energy-efficient compared to ANN, as spikes are sparse.
- Sparse and event-based parallelism.
- Asynchronous spike communication.

Artificial Neural Network

- Information is transmitted through continuous values passed between layers.
- No explicit notion of time; computations are synchronous.
- Computationally expensive, especially with large-scale networks (requires GPUs/TPUs).
- Layer-wise parallelism (often done in GPUs).
- Synchronous communication of continuous values.

Data Encoding

- SNNs process temporal data; encoding converts input signals (e.g., images, audio, biomedical signals) into spike trains for neural computation.

Rate encoding

$$r = \frac{\text{Number of spikes}}{\text{Time window}}.$$

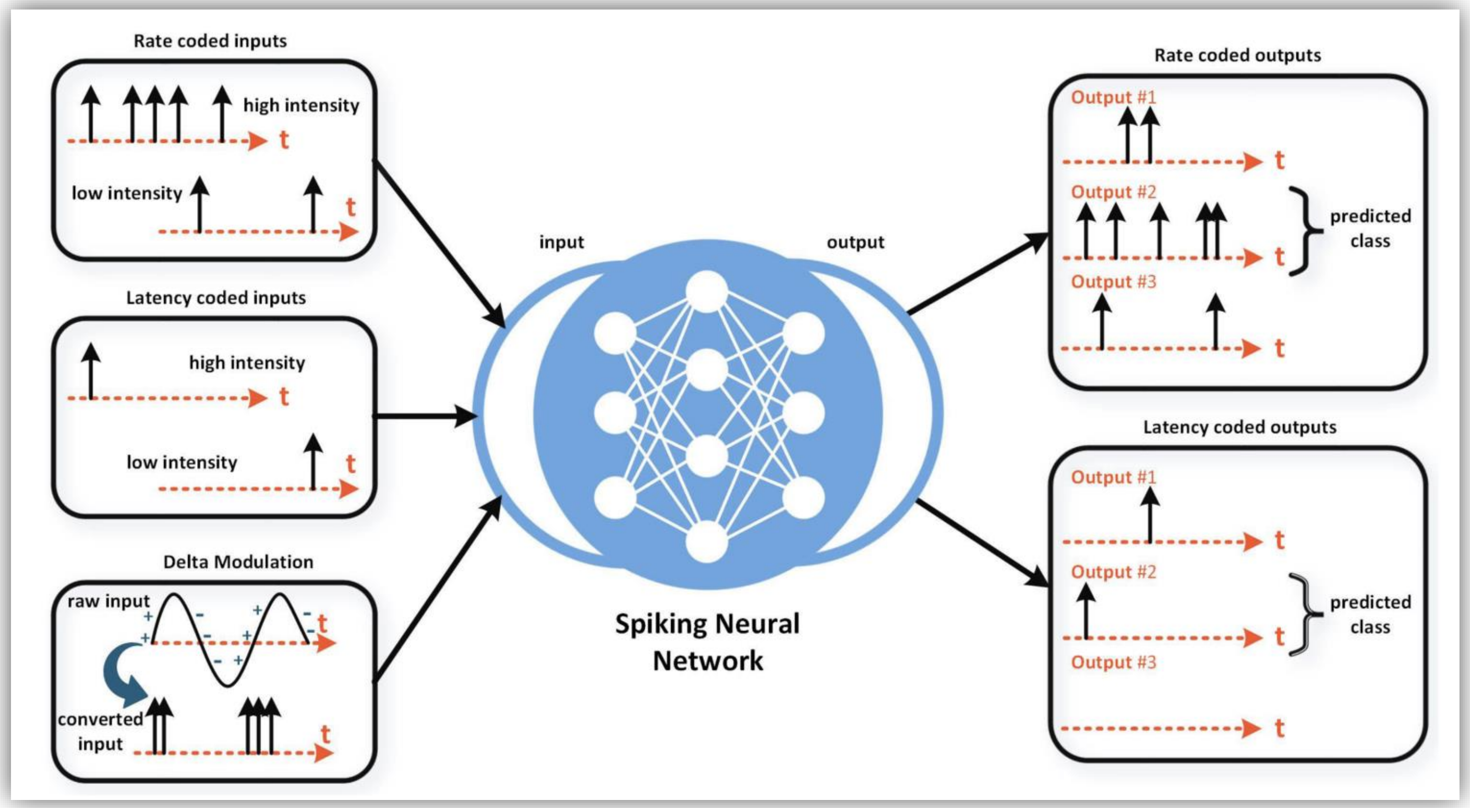
Latency encoding

$$x_i = f(t_i - t_{\text{ref}})$$

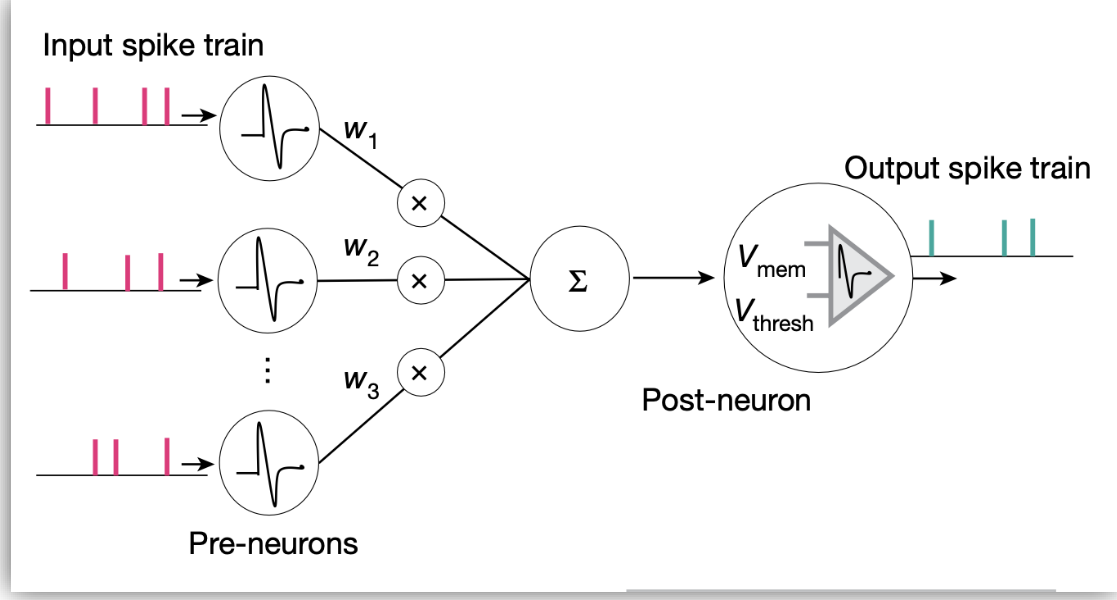
* for images:

```
def apply_latency_encoding(input_data: np.ndarray):
    times = np.maximum(0.0, 1.0 - input_data)
    times[times == 1.0] = np.inf
    return times
```

Data Encoding



Spiking Neuron



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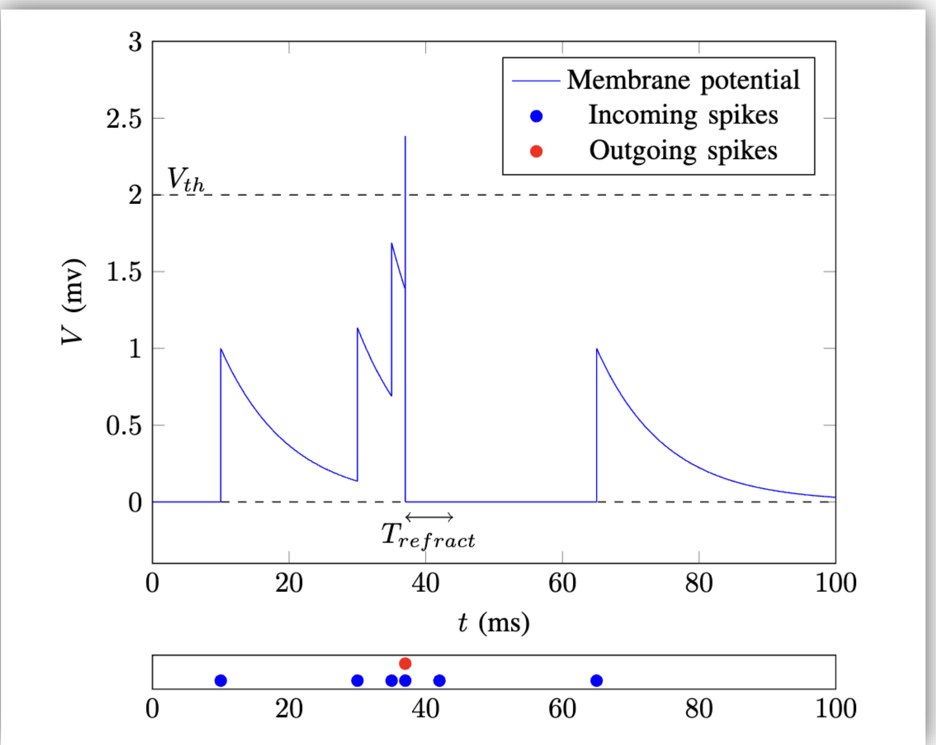
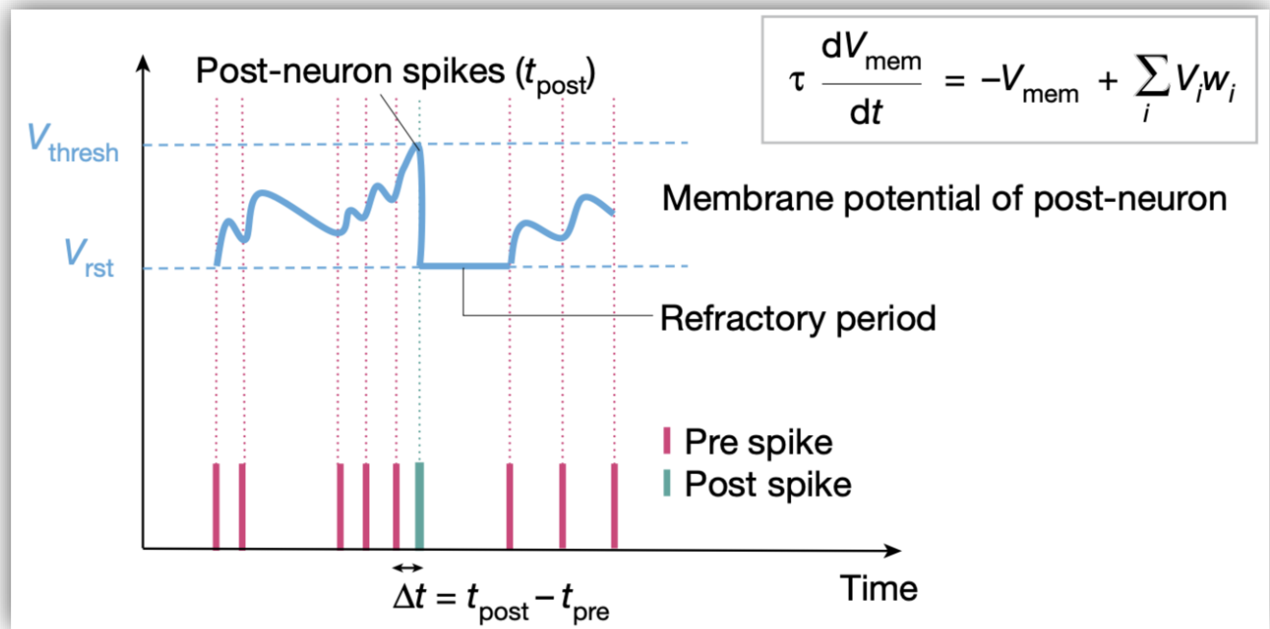
Neuron Model



[5]

Leaky Integrate-and-Fire

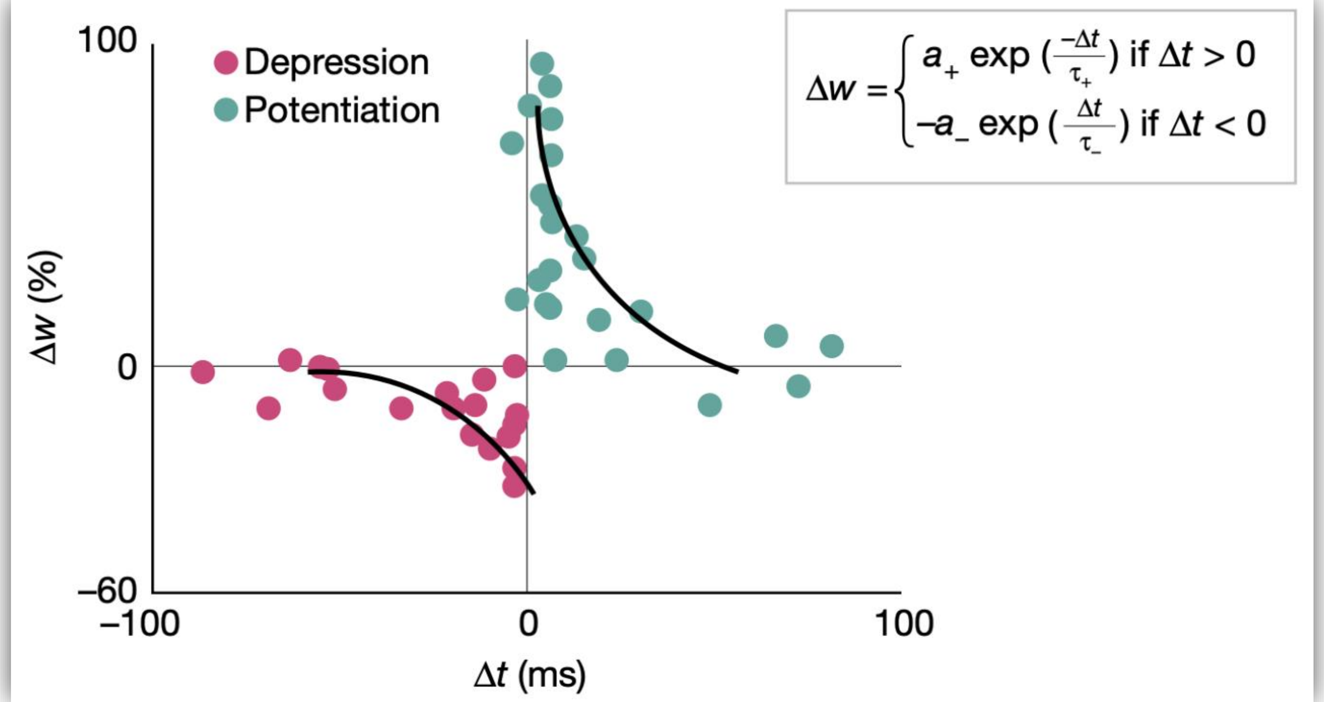
Learning



[1]

LIF Neurons Dynamics

Learning - Unsupervised



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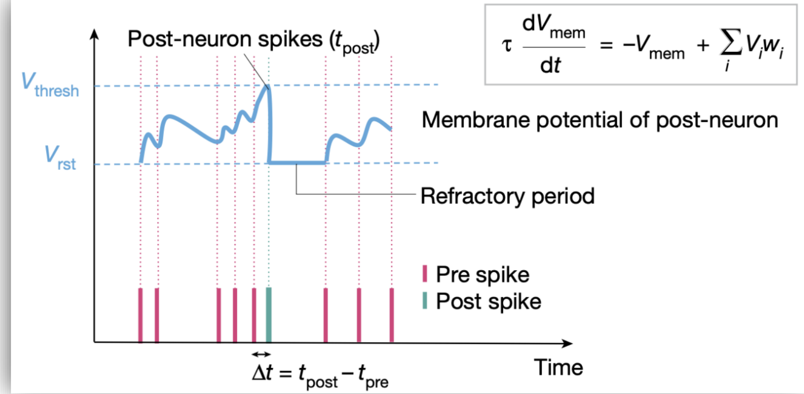
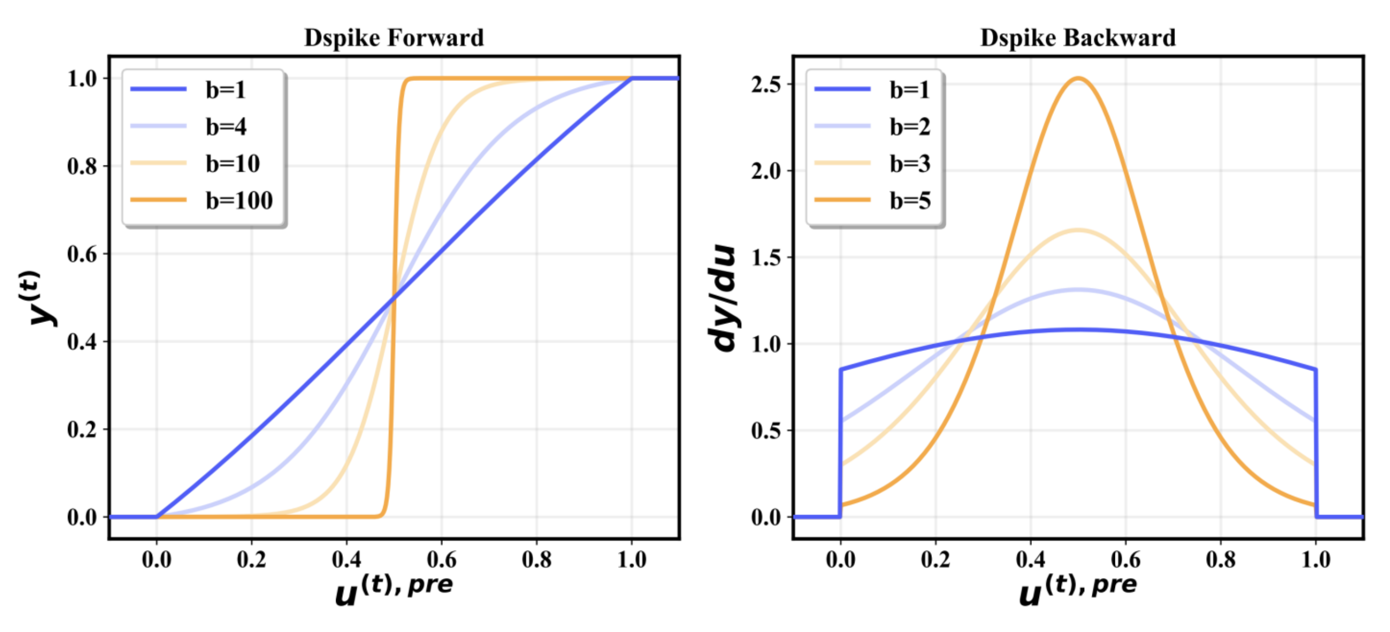
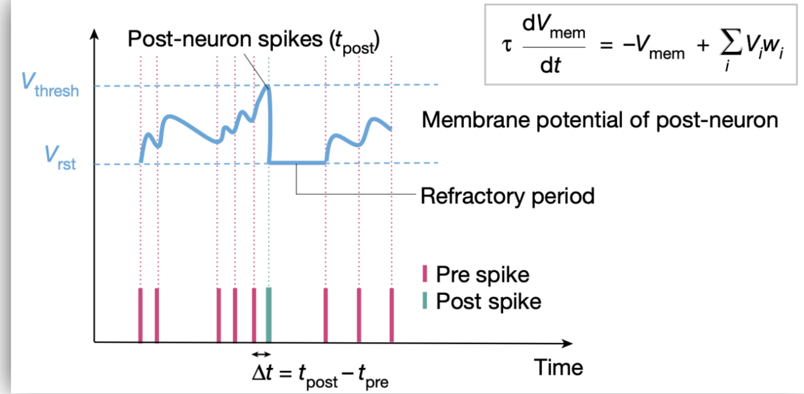


Spike Timing-Dependent Plasticity

Learning - Supervised





Surrogate Gradient Descent

Unsupervised Results on MNIST

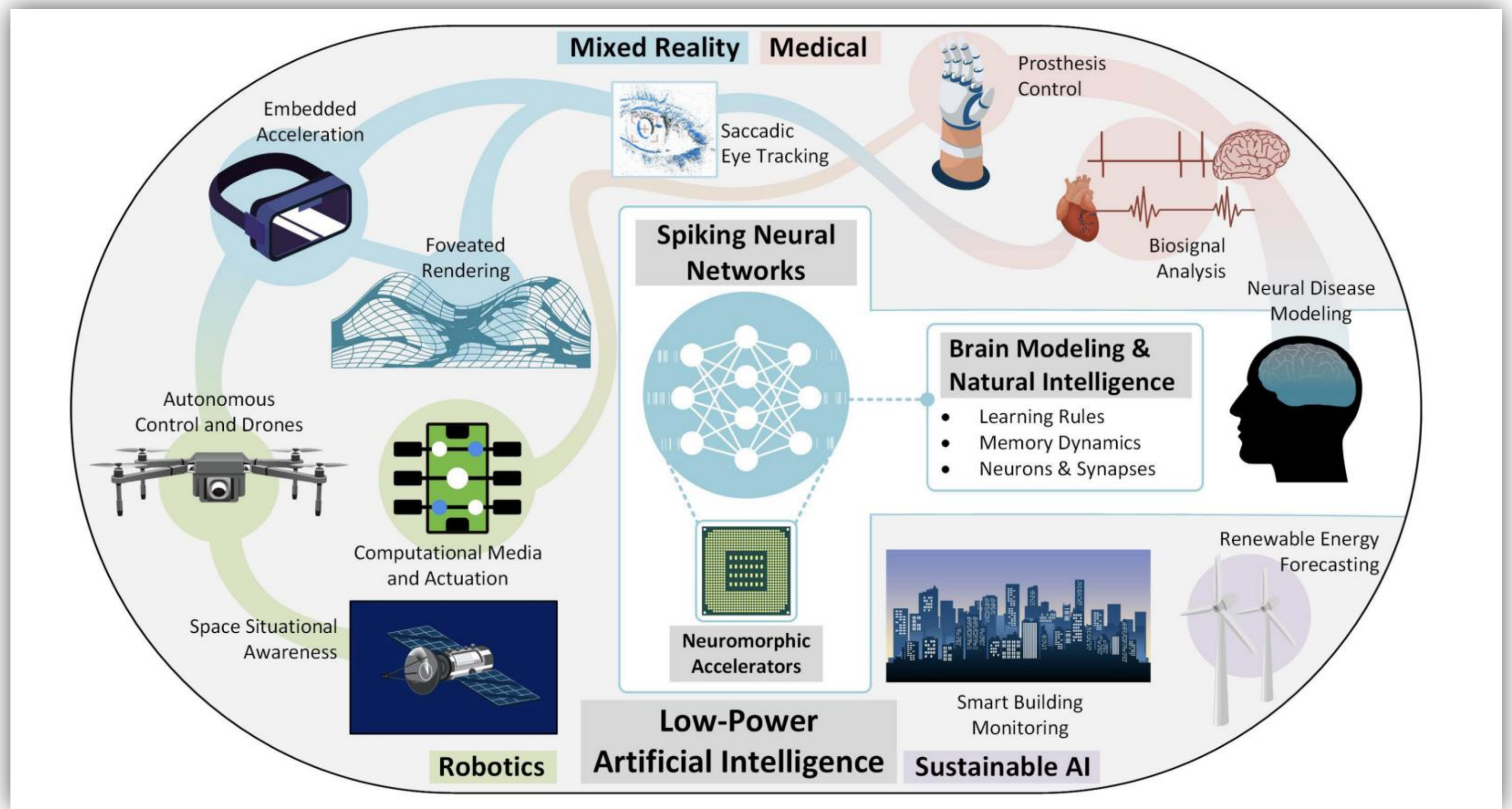
Model	Description	Accuracy
Dielh et al. 2015 [8]	Single Layer SNN	95.0%
Kheradpisheh et al. 2018 [9]	Convolutional SNN + SVM	98.4%
Falez et al. 2019 [10]	Convolutional SNN + SVM	98.6%

Supervised Results on ImageNet

[13]

	Year	Work	Architecture	Time Steps	SNN Acc. (%)
ImageNet	2021	STBP-tdBN [45]	ResNet-50	6	64.88
	2021	Diet-SNN [46]	VGG-16	5	69.00
	2022	TET [48]	ResNet-34	6	64.79
	2022	IM-loss [49]	VGG-16	5	70.65
	2022	TEBN [50]	ResNet-34	4	64.29
	2022	GLIF [52]	ResNet-34	4	67.52
	2022	RecDis-SNN [53]	ResNet-34	6	67.33
	2023	MPBN [55]	ResNet-34	4	64.71
	2023	Attention SNN [59]	ResNet-34	1	69.15

Applications



Research Directions

[6]

So much work still to be done!

Lots of low hanging fruit and possible questions/projects.

Can we make this more efficient?

- Run faster
- Local learning version
- Better scaling
- Sparse connectivity

Computational advantages of SNNs?

- Fast decision making?
- Robust to noise?
- Robust to adversarial attacks?
- More generalisable?
- Low power (neuromorphic computing)

Answer biological questions?

- What is the role of spikes?
  Just energy efficiency / transmission?
- Local learning rules
- Interaction with synapse/neuron dynamics

Conclusions

Promise of SNNs

- Spiking Neural Networks (SNNs) represent a paradigm shift toward biologically plausible, energy-efficient computation.
- Their ability to process spatiotemporal data with sparse activity makes them ideal for real-time and low-power applications.

Challenges

- Training complexity, scalability issues, and hardware limitations remain barriers.
- Accuracy lags behind traditional ANNs for large-scale datasets.

Advancements

- Progress in training methods (e.g., surrogate gradients, STDP) has improved performance and scalability.
- Hybrid architectures combining SNNs and ANNs are bridging the gap in accuracy for complex tasks.

Future Directions

- Development of more scalable training algorithms for deeper SNNs.
- Advancements in neuromorphic hardware to handle larger and more complex networks.
- Targeting niche areas (e.g., robotics, biomedical devices) to capitalize on SNN strengths.

Thanks for your attention!

Q&A time

Bibliography

[1] Roy, Kaushik, Akhilesh Jaiswal, and Priyadarshini Panda. "*Towards spike-based machine intelligence with neuromorphic computing.*" Nature 575.7784 (2019): 607-617.
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[8] Eshraghian, Jason K., et al. "*Training spiking neural networks using lessons from deep learning.*" Proceedings of the IEEE (2023).