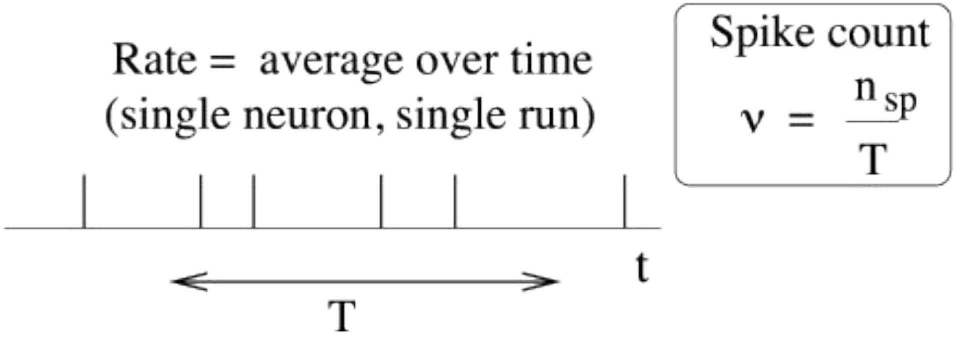
Introduction to Spiking Neural Networks

Basics from Neuroscience

Reference for figures:

Auge, Daniel & Hille, Julian & Mueller, Etienne & Knoll, Alois. (2021). A Survey of Encoding Techniques for Signal Processing in Spiking Neural Networks. Neural Processing Letters. 53. 10.1007/s11063-021-10562-2.

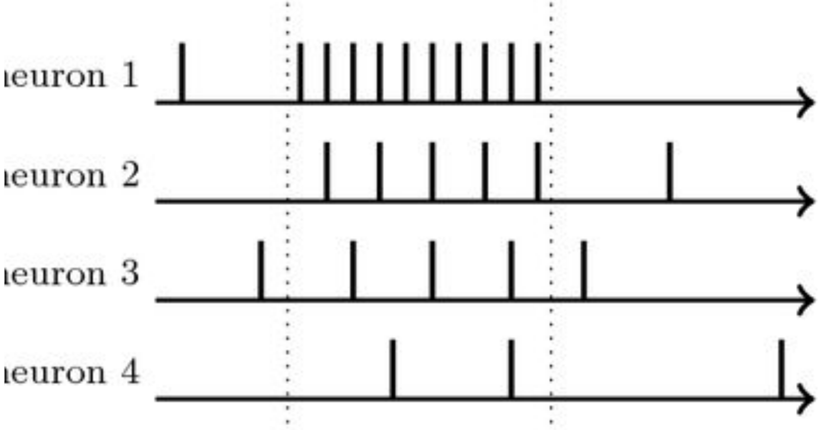
Feature Analysis of Spiking Encoding Sequence



Rate Coding

- Transforms discrete spiking information into continuous firing frequency representations by aggregating spike activity over time windows.
- Enhances robustness against noise interference, making rate coding widely adopted in SNNs.
- Sacrifices parallel processing capabilities, increases processing time, and reduces the efficiency of information transmission.

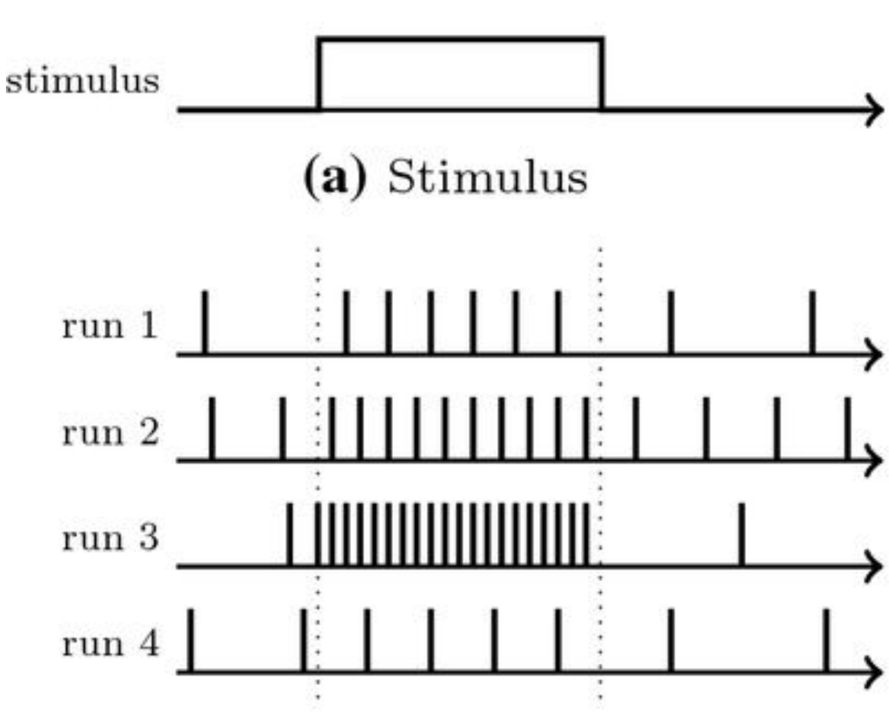
(b) Count rate coding



(d) Population Rate coding

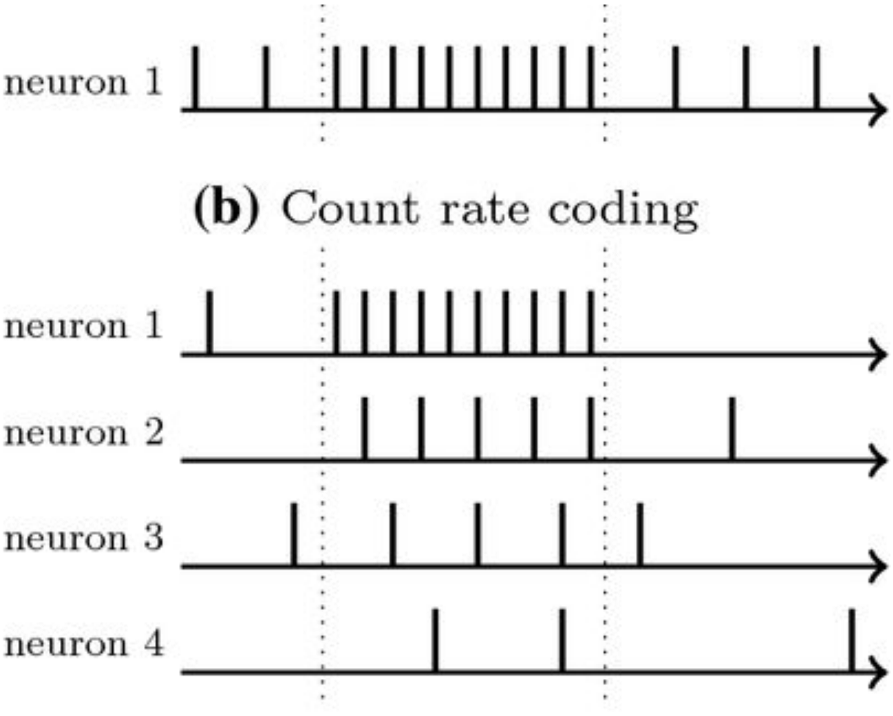
Feature Analysis of Spiking Encoding Sequence

Density Rate Coding



(a) Stimulus

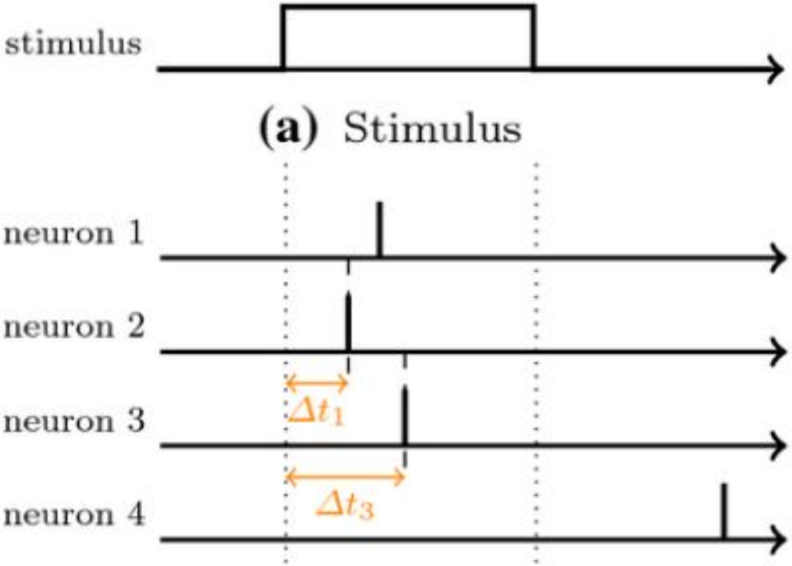
Population Rate Coding



(b) Count rate coding

Direct time coding encodes information based on the **precise** timing of spike emissions.

- Time-step-based: encodes information at discrete time points {t0, t1, ..., tn}
- Continuous time coding utilizes ***actual*** spike timestamps



The encoder encodes **the input data x** by emitting a **spike with a delay.** The **greater the stimulus** intensity, the ***earlier* the spike is fired**, with a predefined maximum spike time.

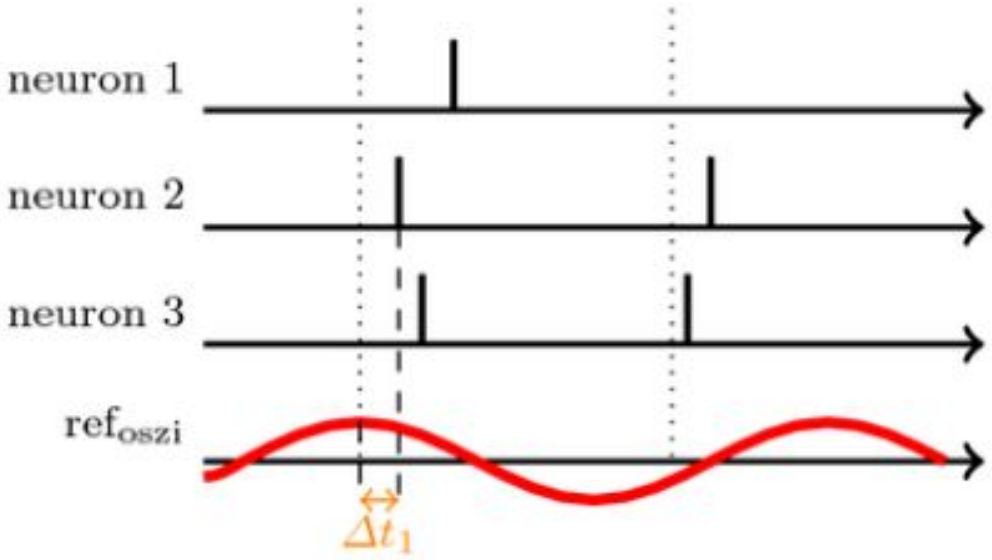
For input x, a spike sequence with a time window equal to the maximum spike time is generated, in which exactly one spike is emitted, e.g., **stimulus intensity x** $\in [0, 1]$,

$tf(x) = (T - 1)(1 - x)$

$tf(x) = (T - 1) - \ln(\alpha x + 1)$.

Phase Coding

- Encodes information by comparing spike times to a **global oscillatory reference,** utilizing **phase differences** for encoding.
- Supported by biological evidence in neural recordings.



Other Spike Time-based Coding Schemes

- **Rank Order Coding (ROC)** encodes information based on the ***relative timing*** of spikes ***among multiple* neurons**.
- Retinal studies suggest that ROC is more biologically plausible than TTFS, as the brain may not have access to an absolute stimulus onset time (*).
- **Population Neural Relative Timing (PNRT)**, variant of ROC, encodes numerical values through spike timing differences across neurons, enhancing sparsity and biological realism.
- **Inter-Spike Interval (ISI) Coding**, which encodes delays between consecutive (**)
- **Synchrony coding** conveys information through simultaneous spike emissions

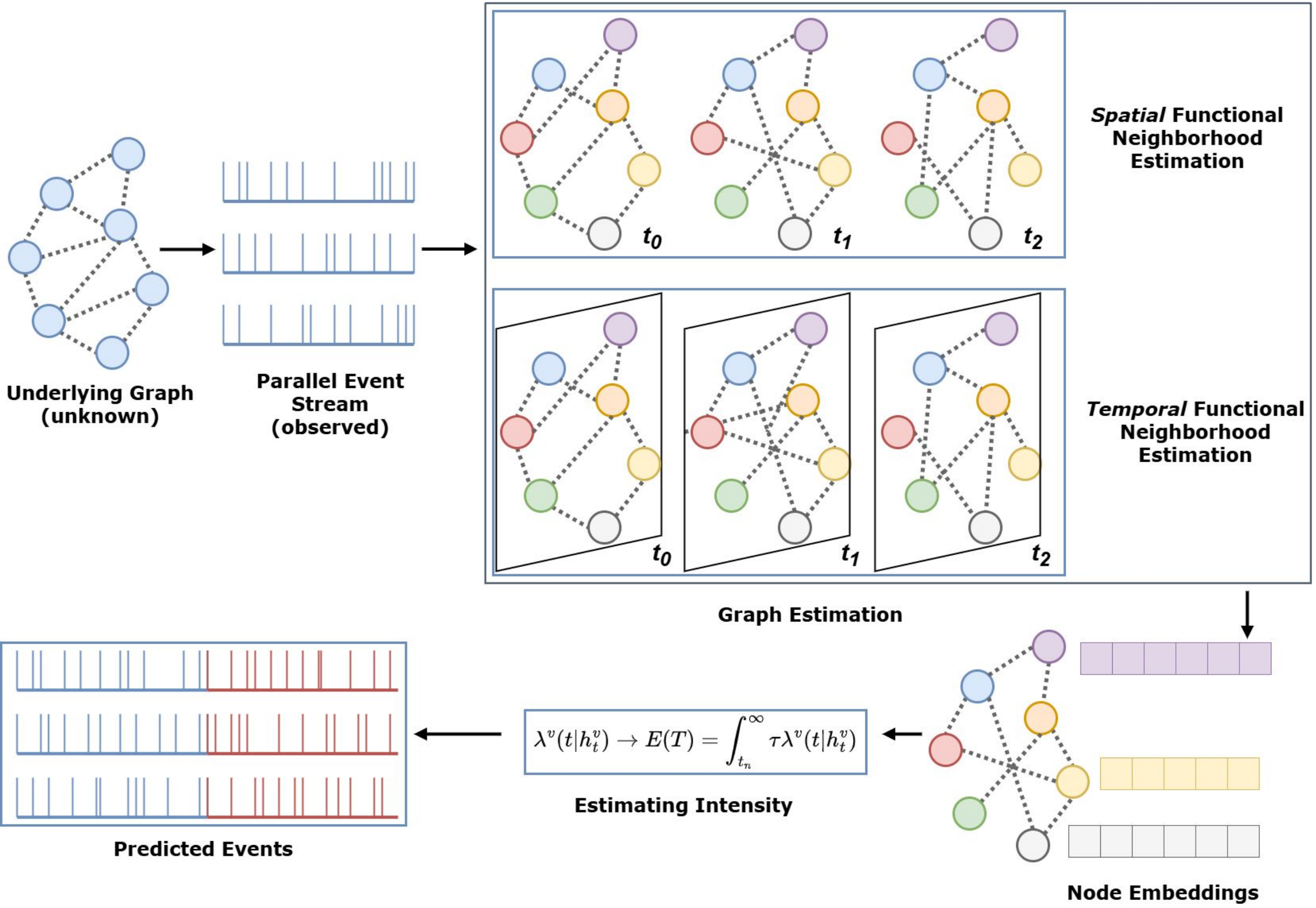
Multivariate Encoding Methods

- Multivariate encoding methods do ***not*** restrict information encoding to a specific feature space but instead aim to achieve a more ***comprehensive spike sequence representation***.
- **Direct encoding,** a common multivariate encoding approach, maps **input features directly onto spike timing** or spike trains **without additional transformation layers**, thus preserving as much information as possible within the temporal structure of spikes, leading to more biologically plausible and efficient information processing.
- In direct encoding, example of neuron models to facilitate this process:

  Integrate-and-Fire (I&F) neurons accumulate input signals until a threshold is reached, resulting in a spike, thereby directly translating input intensities into spike timings.

  Leaky Integrate-and-Fire (LIF) neurons introduce a ***leakage term***, allowing the model to account for the **decay of membrane potential over time**, which adds a layer of biological realism to the encoding process.

The **unknown underlying graph** generates a **parallel event stream** (observed as **spike trains**).
The ***spatial* and *temporal* functional neighborhoods** can be estimated from the observed events, dynamically constructing an evolving graph representation.



Predict future events based on **learned spatio-temporal dependencies.**

$$\boxed{\lambda^v(t|\mathcal{H}_t) = f\left(\sum_{u \in \mathcal{N}(v)} \alpha_{uv}(t) h_u(t) + \beta_v \delta(t - t_n)\right)}$$

h_u(t): neural embeddings derived from membrane potentials

α_{uv}(t): learned attention weights capturing dynamic node interactions
β_u: models type-specific effects
f(.): non-linear activation