SMU
SINGAPORE MANAGEMENT UNIVERSITY

School of
Computing and
Information Systems

Neuromorphic Systems Project

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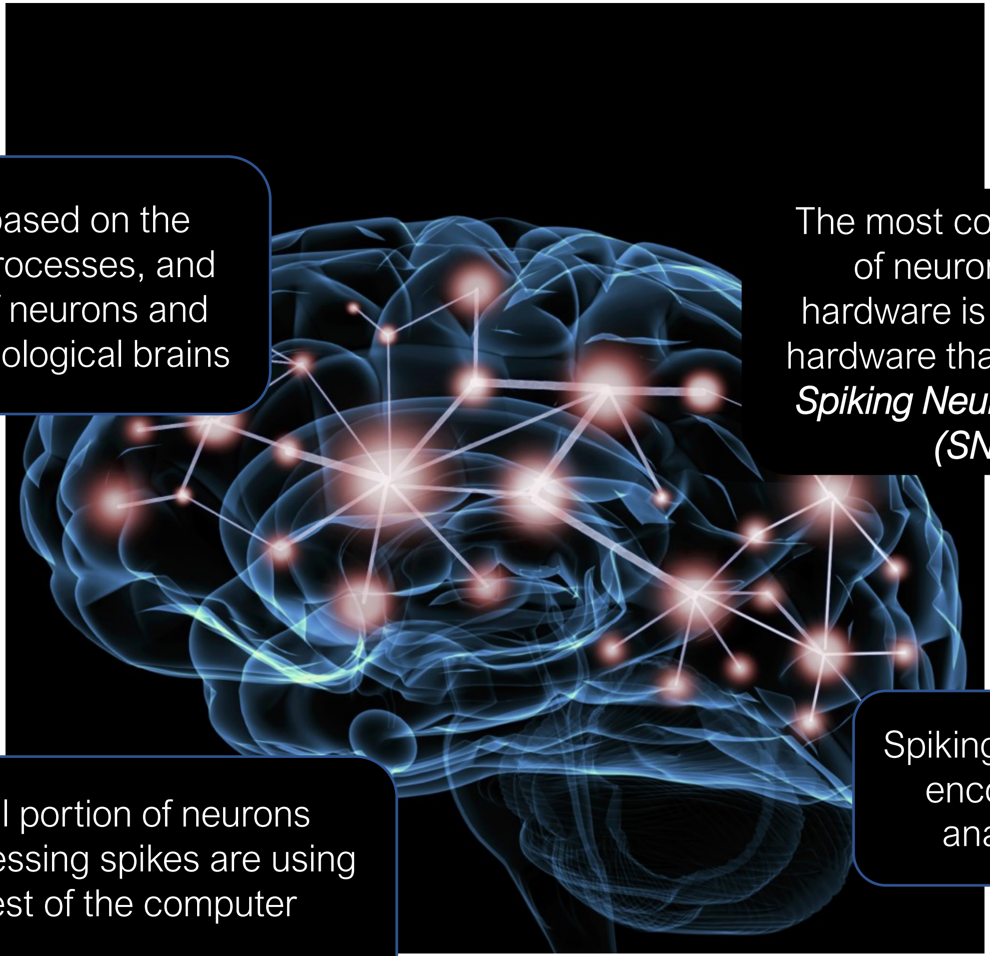
08/05/2023

Neuromorphic Computing



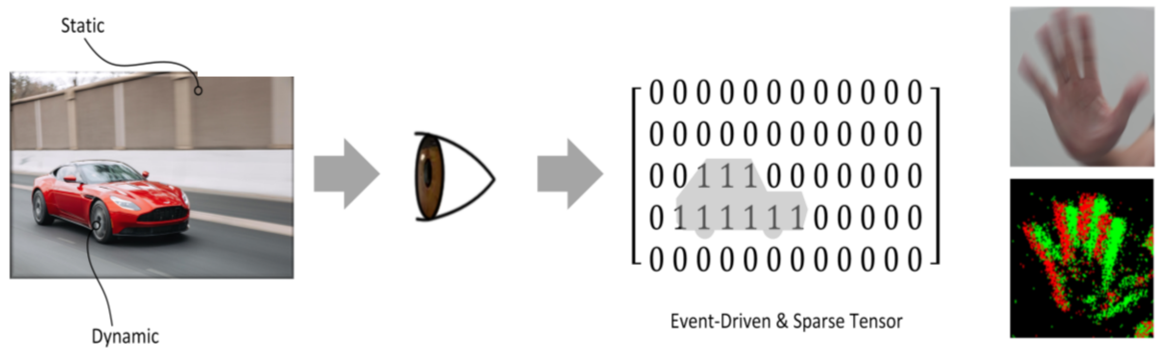
Hardware based on the structures, processes, and capacities of neurons and synapses in biological brains

The most common form of neuromorphic hardware is the spiking hardware that implement *Spiking Neural Network (SNN)*

Spiking neurons measure and encode only the discrete analog *signal changes*

Only the small portion of neurons actually processing spikes are using energy; the rest of the computer remains idle

Neuromorphic Vision



The retina doesn't send picture frames;
it preprocesses the light and transmits only changes in light intensity

Each pixel responds to illumination changes asynchronously

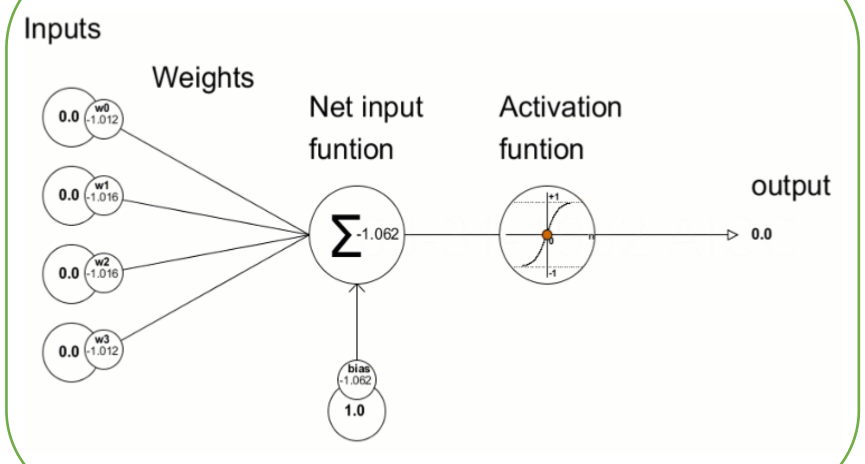
Output data stream is sparse (computation and energy efficient)

Fast response (Asynchronous)

Sensitive to extreme light conditions

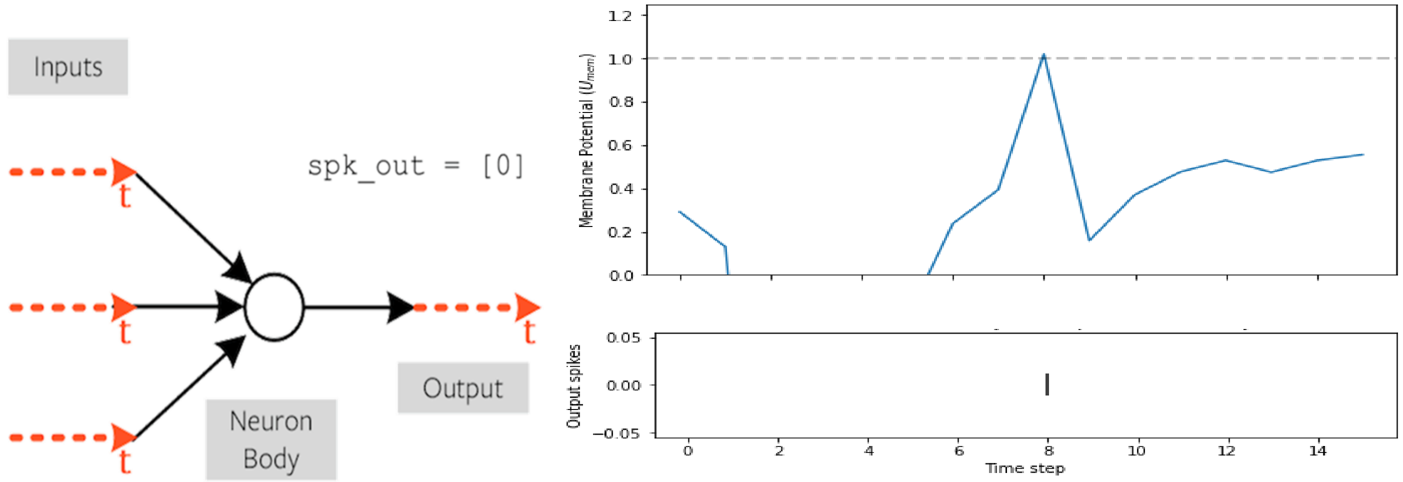
ANN Vs SNN

Standard Artificial Neuron



Ignores the time domain complexity of the brain

Spiking Neuron



Maps state and time to spikes

Project Goals

Identify how static data can be used in SNNs
(MNIST data)

Identify how event-based data can be used in SNNs
(NMNIST data)

Carrying out classification tasks with SNNs
(with different spatial interpolation techniques)

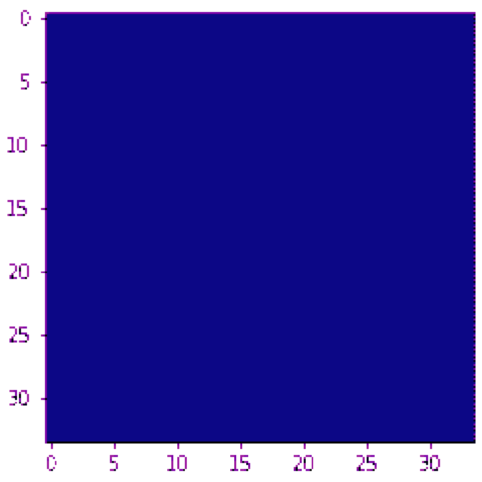
Carrying out object detection tasks with SNNs
(with different spatiotemporal interpolation techniques)

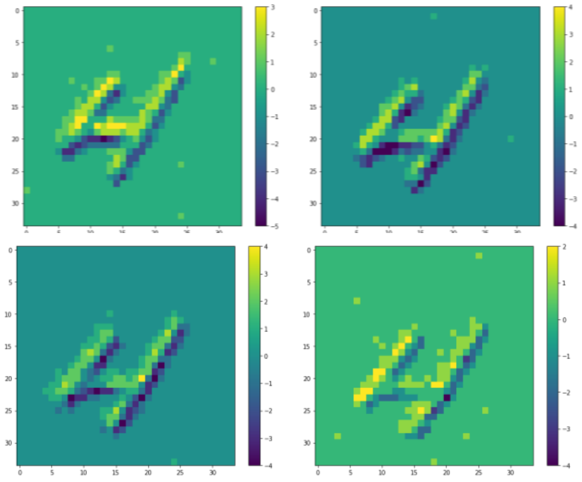
Identifying the effects of spatiotemporal compression of event data on Machine Learning model accuracy

Methods of Incorporating ML to Neuromorphic Data

Create frames using the events and feed them to existing deep networks. Frames are generated on demand (no events = no frames)

Develop event-based AI algorithms





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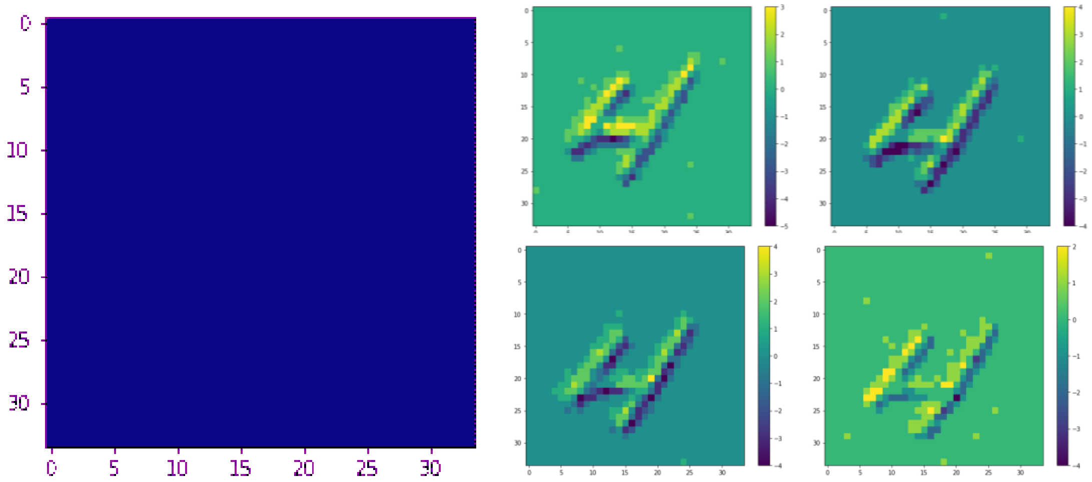
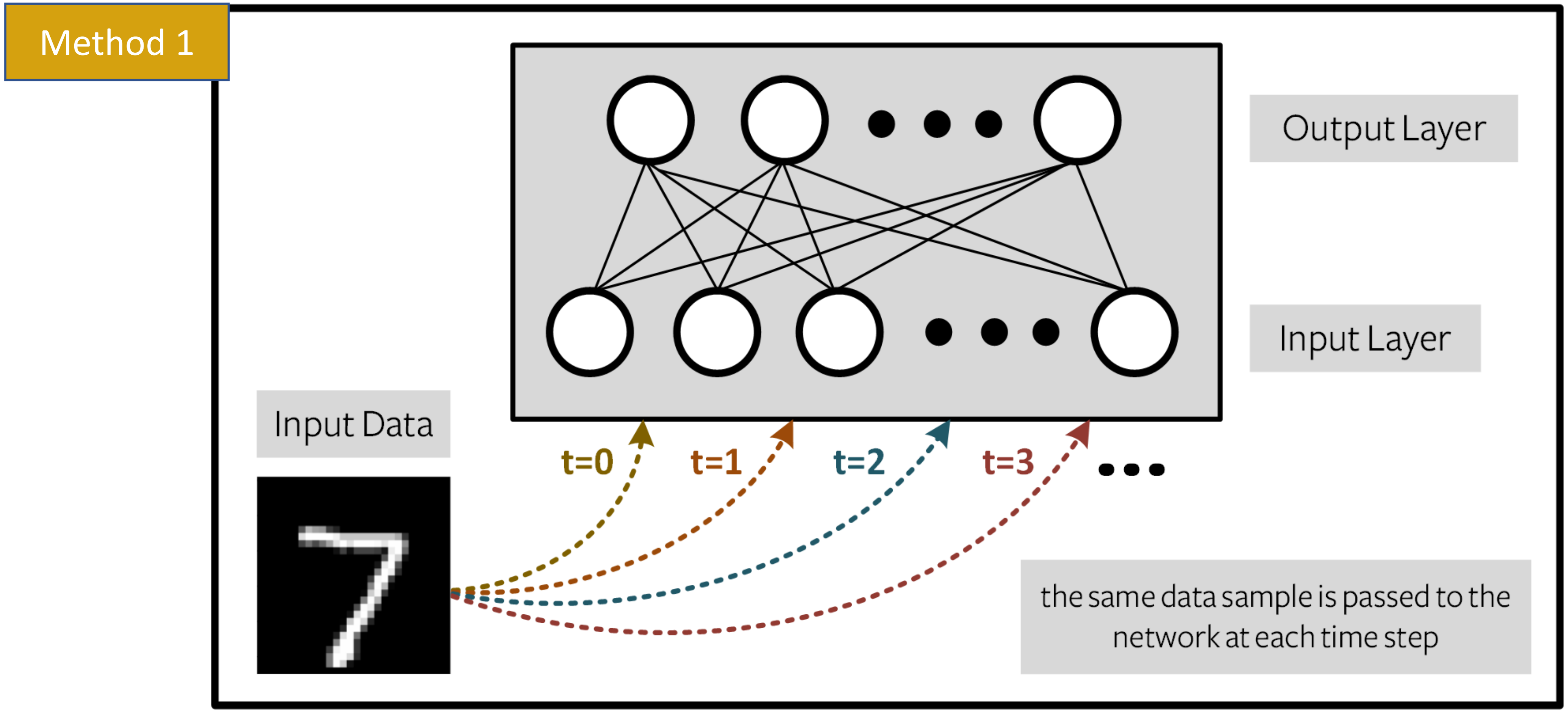
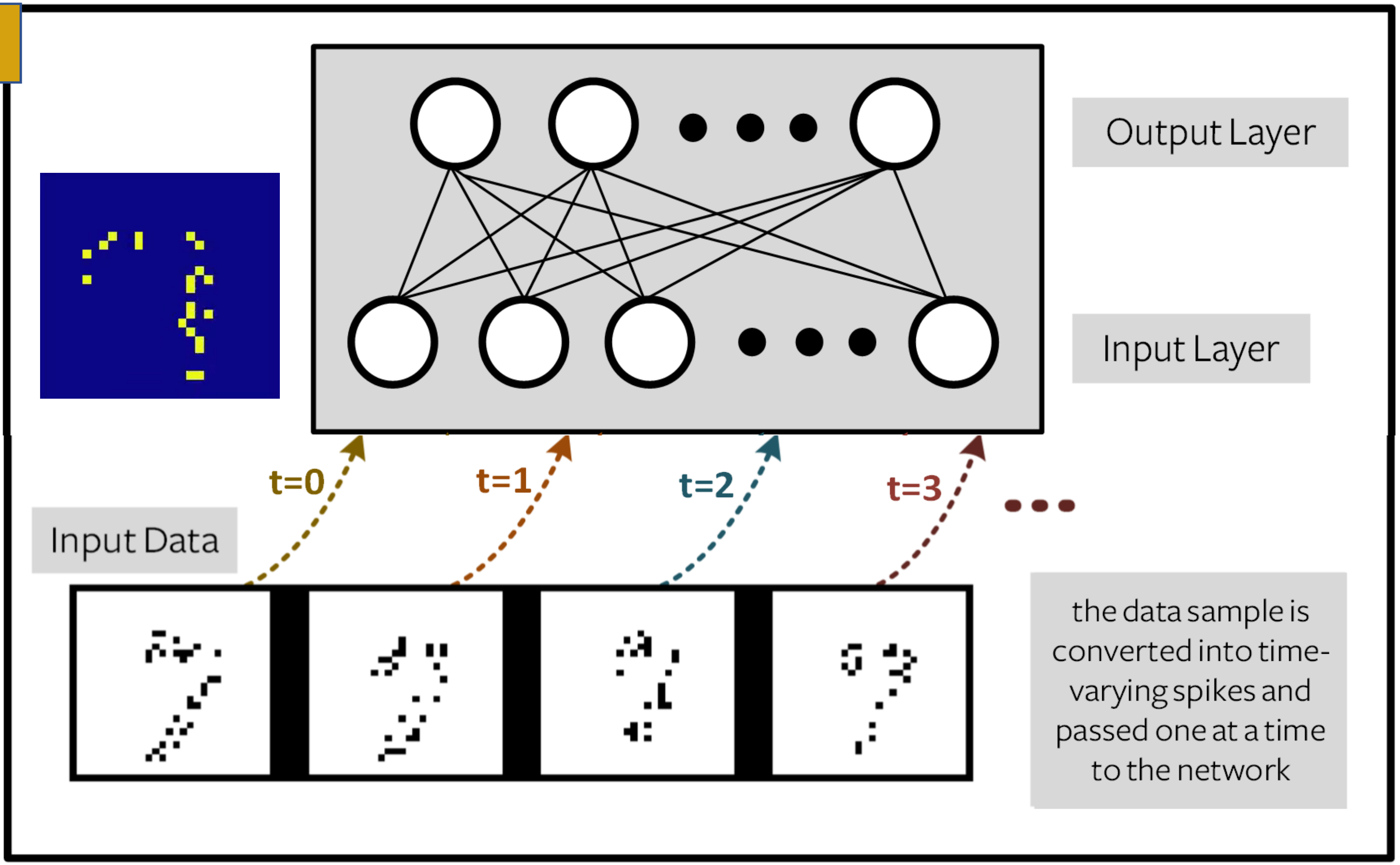


Encoding Static Data into Spike Frames

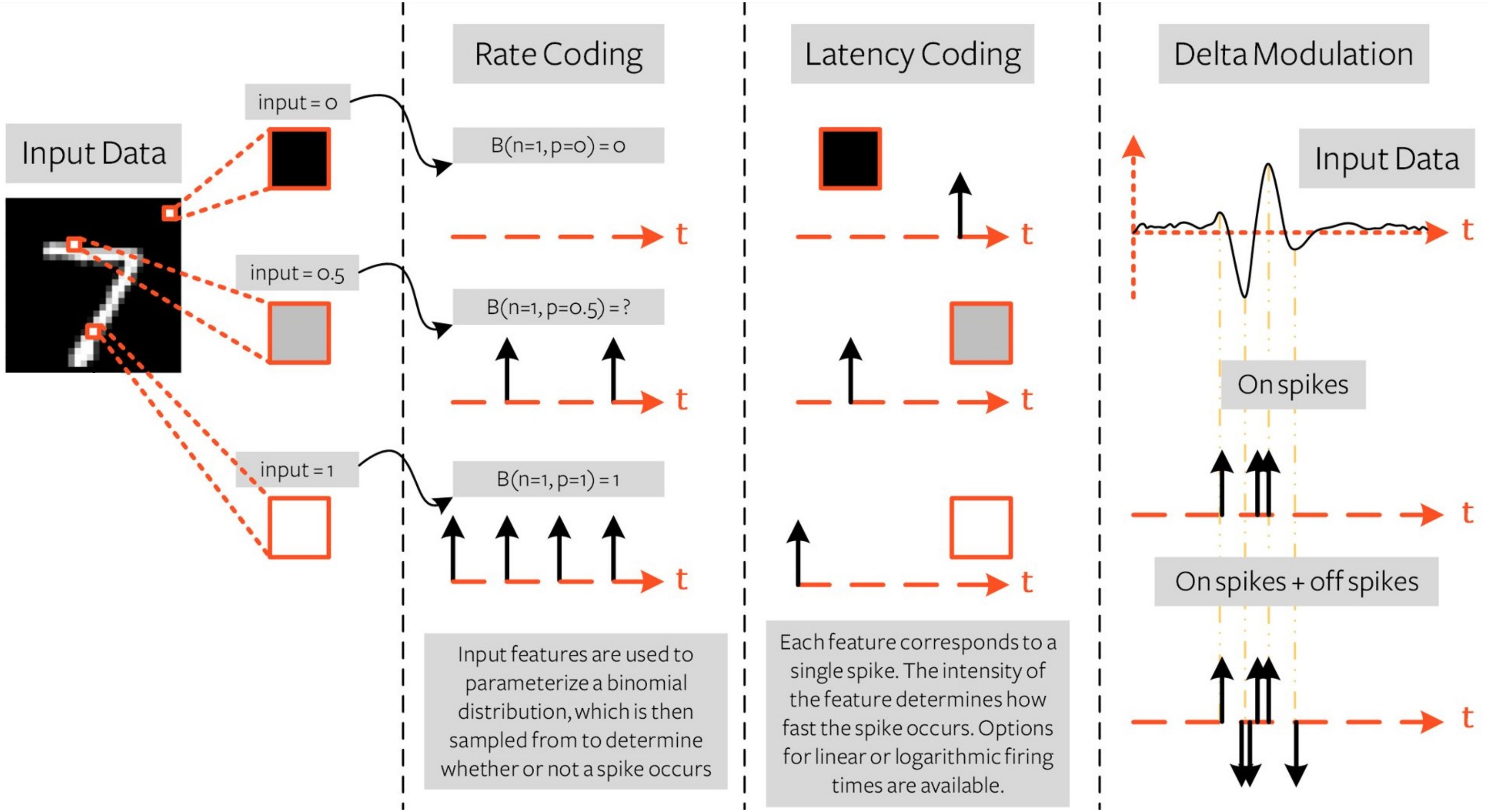


Encoding Static Data into Spike Frames

Method 2



Method 2 explained



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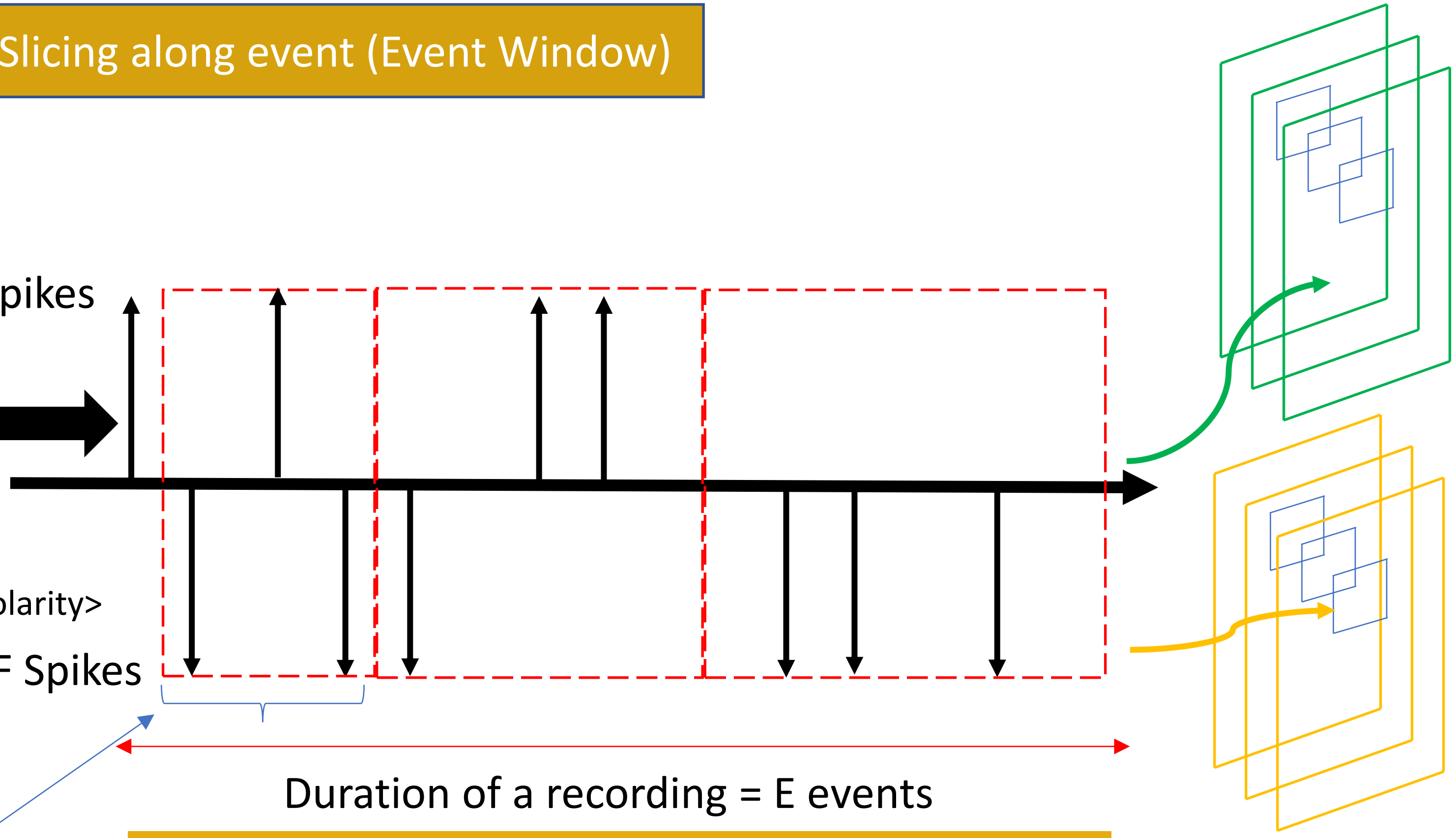
Accumulating Event Data to Frames

Method 1: Slicing along event (Event Window)

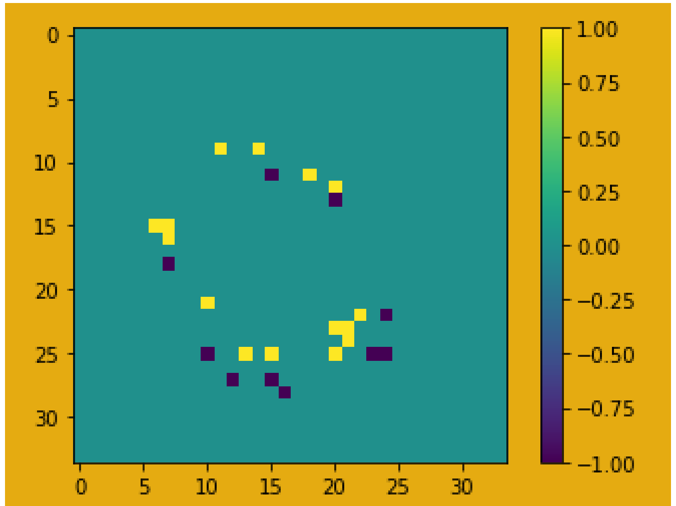
Stream of events in the AER (Address Event Representation) format:

<x, y, timestamp, polarity>



To create S frames from a recording, wait for n number of events (for this example: n = 3)

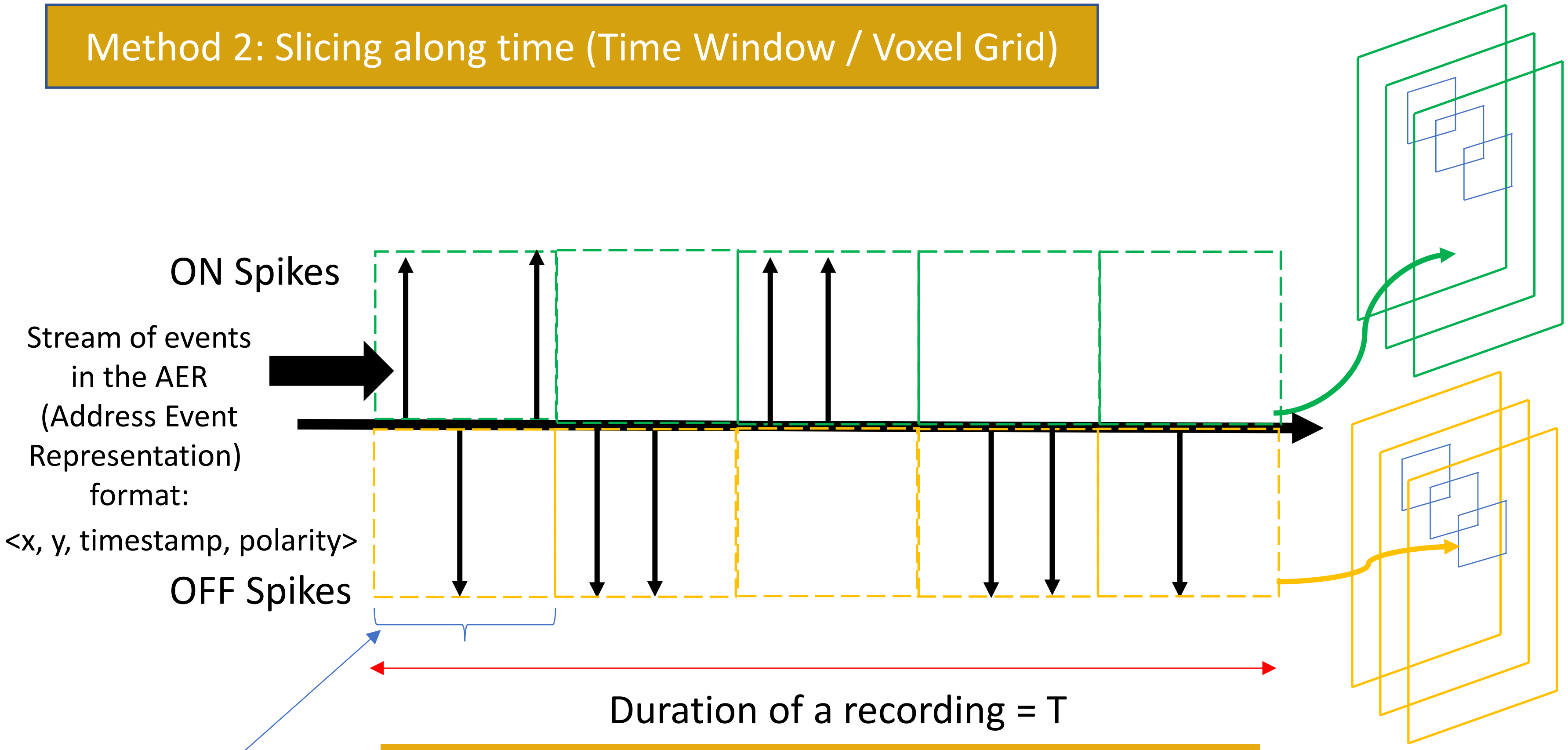
The number of frames is created by waiting for a fixed number of events to occur
$S \in [25, 50, 75, 100, 125, 150, 175, 200]$



Visualization of the two channels of a frame (event_count =25)
+1 → On-spikes (increase in brightness)
-1 → Off-spikes (decrease in brightness)

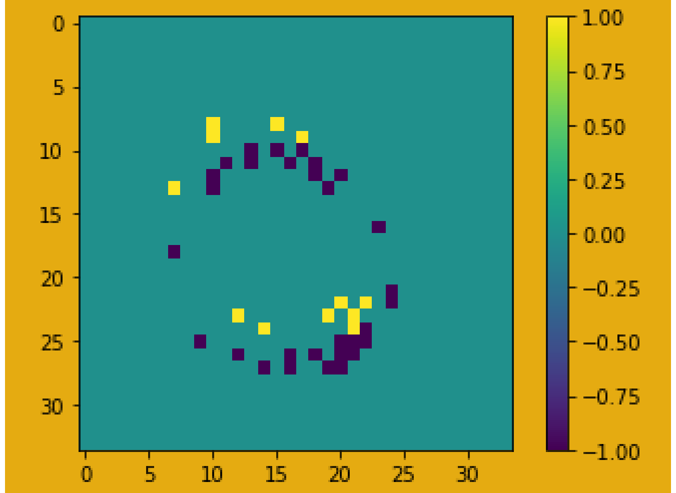
Accumulating Event Data to Frames

Method 2: Slicing along time (Time Window / Voxel Grid)



To create S frames from a recording of length T, divide all the spikes into S time bins

The number of frames that represent the number of timesteps is created by dividing the event stream into S bins
$S \in [1ms, 2ms, 4ms, 6ms, 8ms, 10ms, 12ms, 14ms, 16ms]$



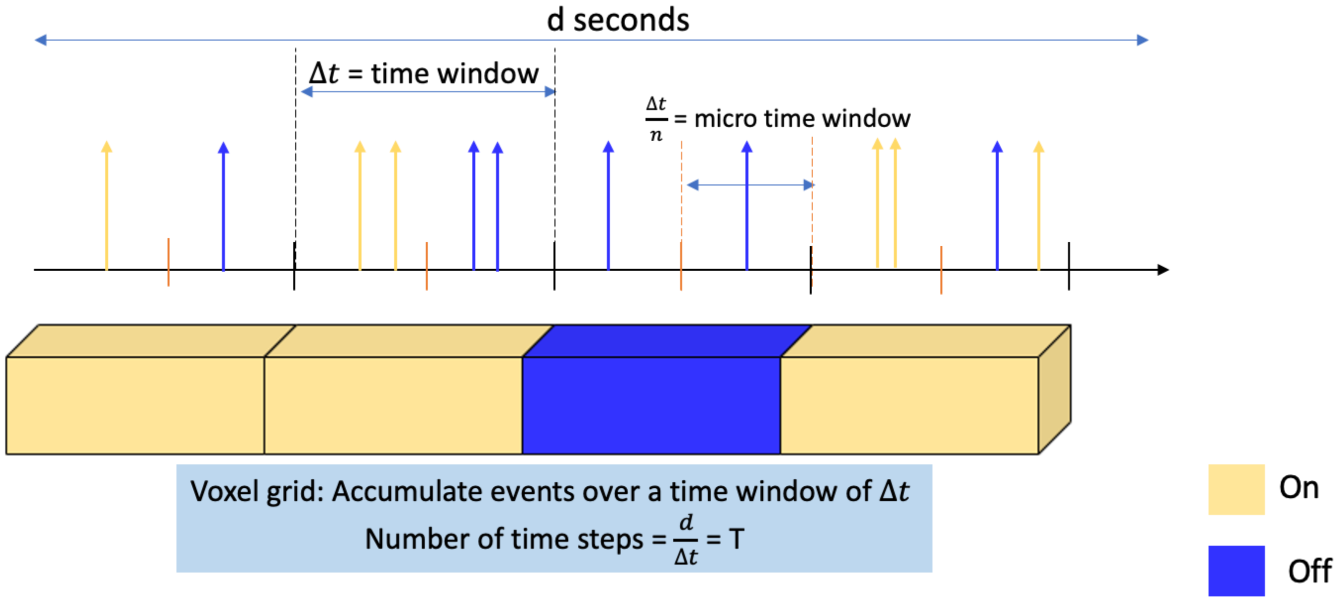
Visualization of the two channels of a frame
+1 → On-spikes (increase in brightness)
-1 → Off-spikes (decrease in brightness)

Accumulating Event Data to Frames

Method 3: Voxel Cubes

To get high temporal resolution of event data with voxel grids, we need to have a large number of timesteps.

This increases linearly the number of computations of the SNN and thus the inference time and the energy consumed.

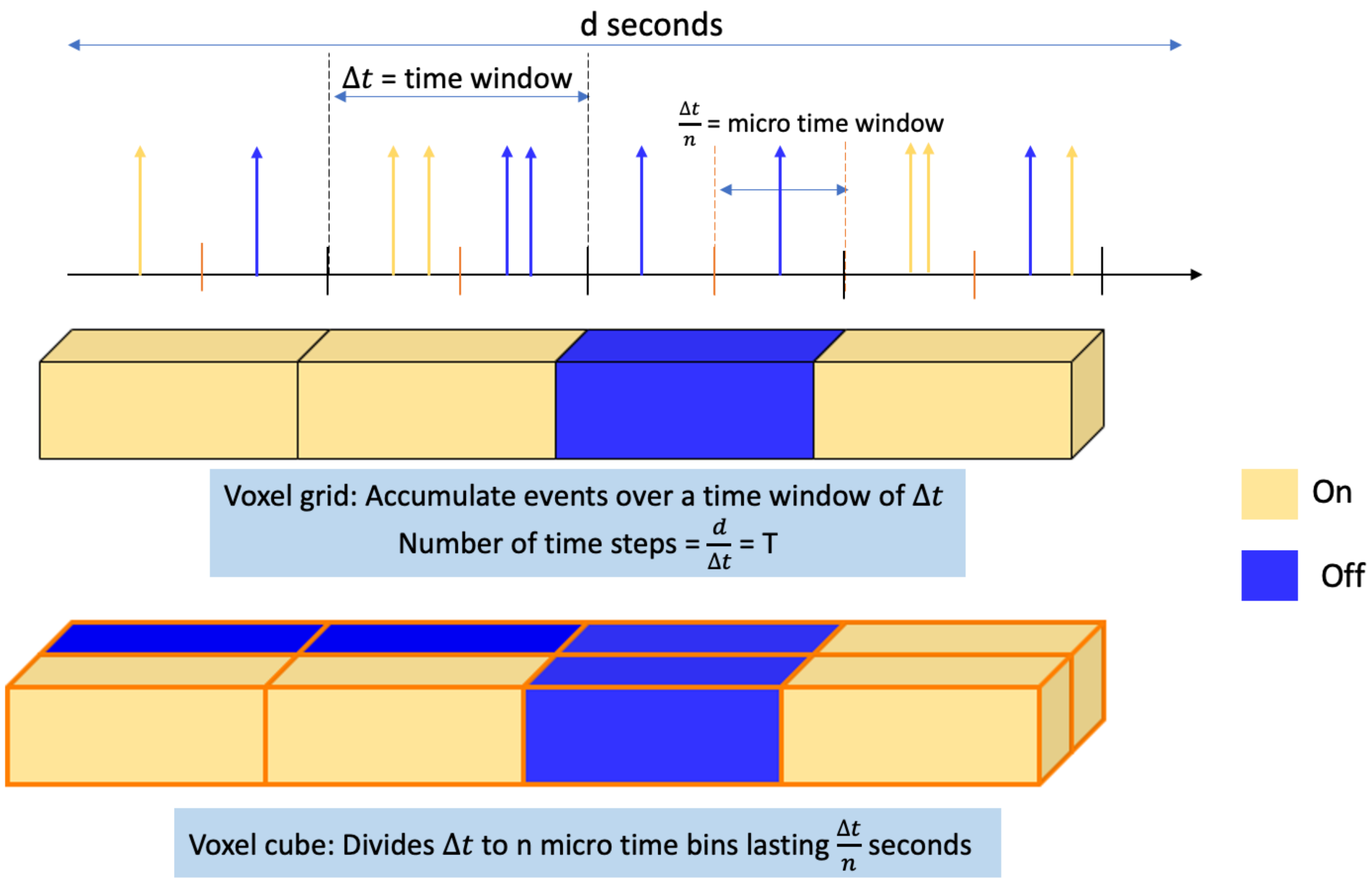


Accumulating Event Data to Frames

Method 3: Voxel Cubes

In voxel cubes, each time window Δt is subdivided into n micro time bins

Events belonging to a micro time bin will be stored in the channels dimension, providing finer temporal information to the first layer of the network.



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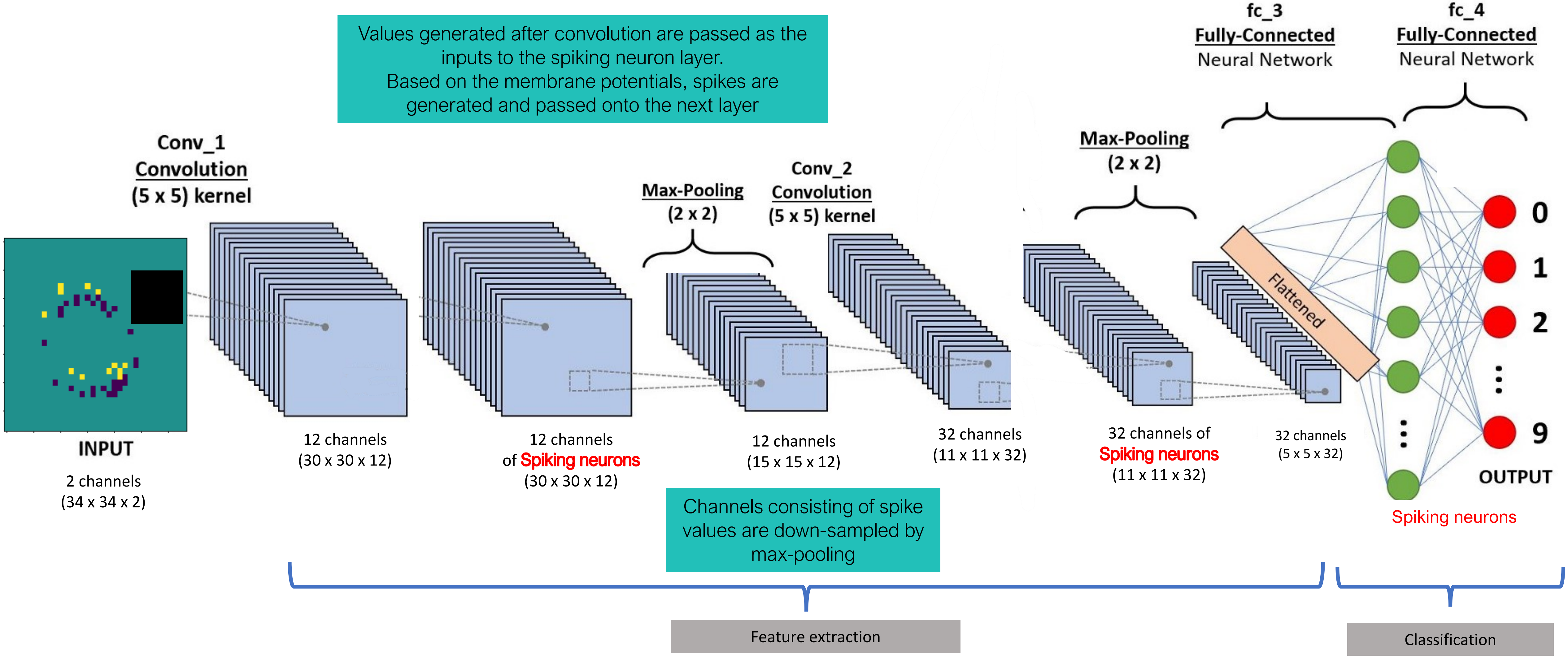
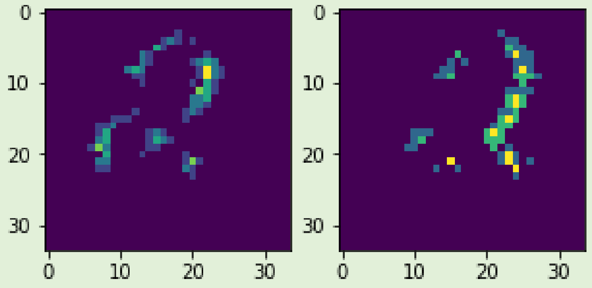
SNN for Classification: Convolutional SNN

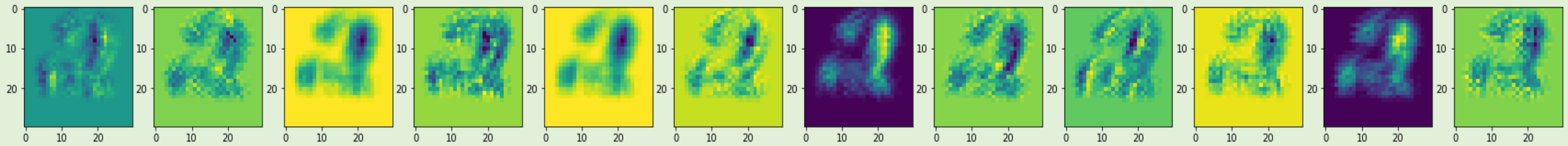


At t=14

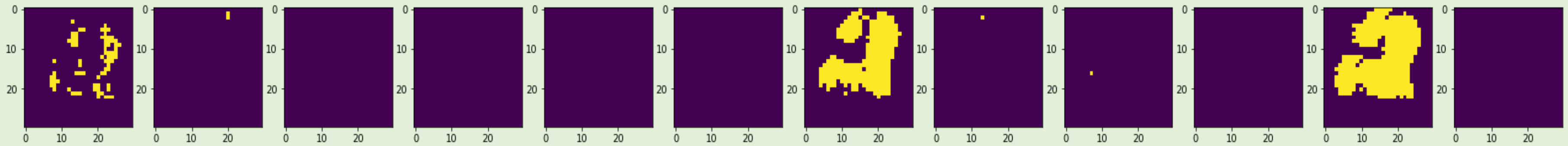
Input (2 channels)

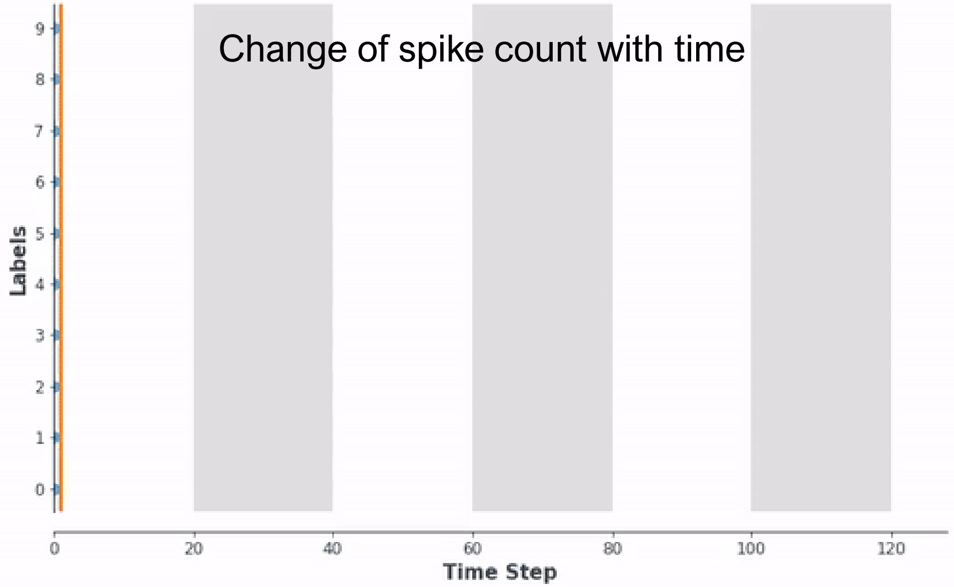


Convolution layer 1 output (12 channels)



Spiking neuron layer 1 spiking output (12 channels)





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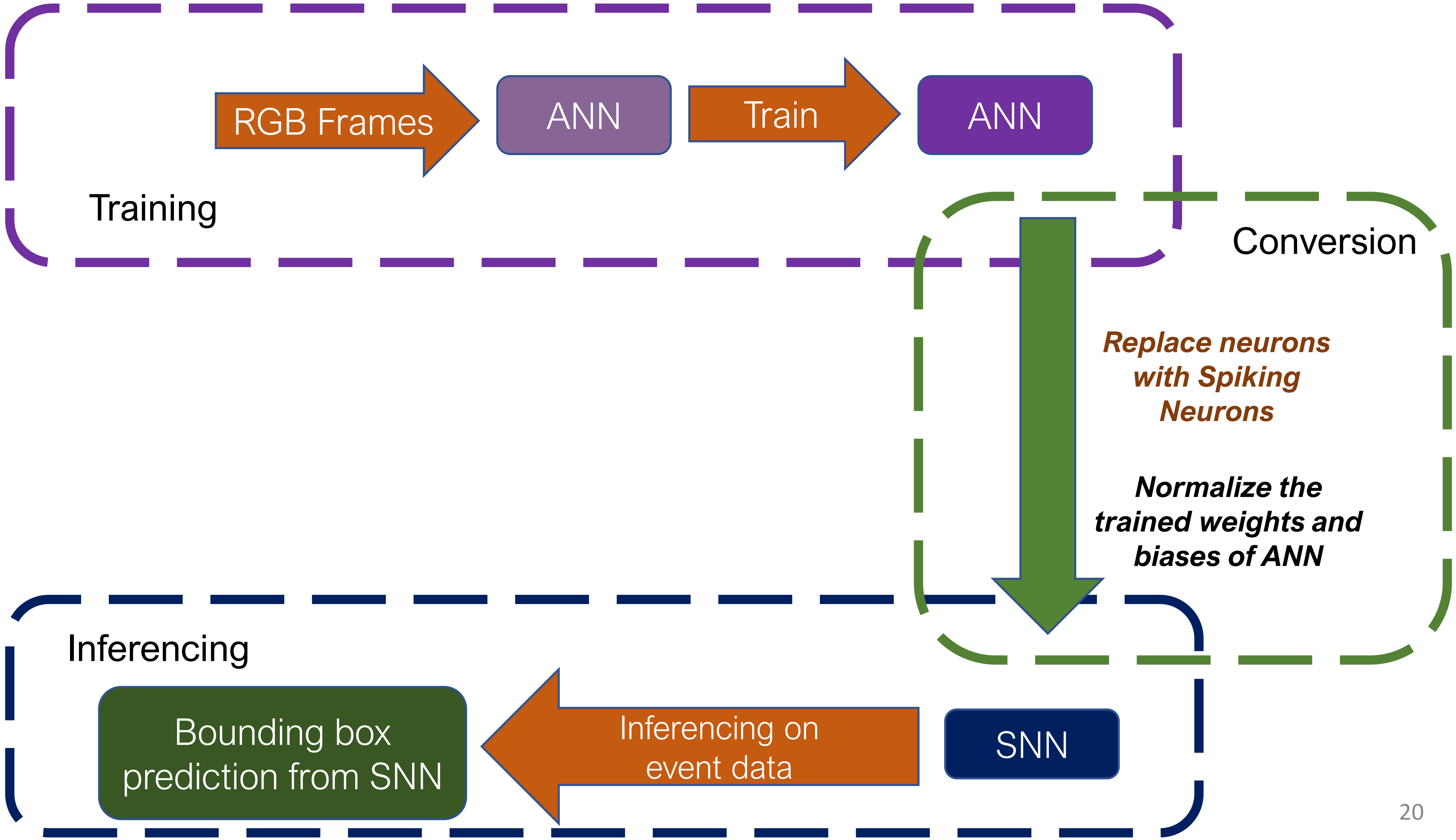
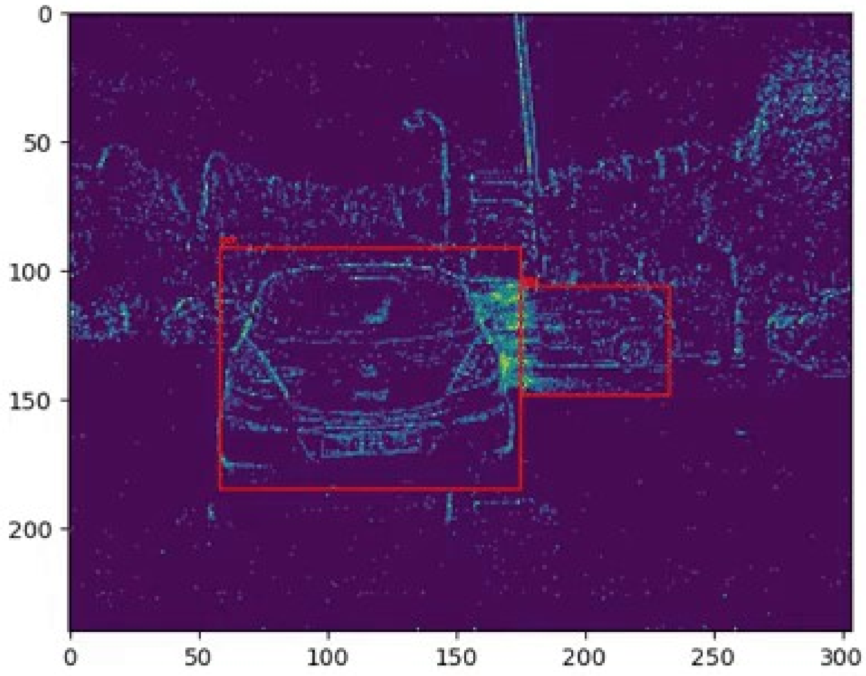
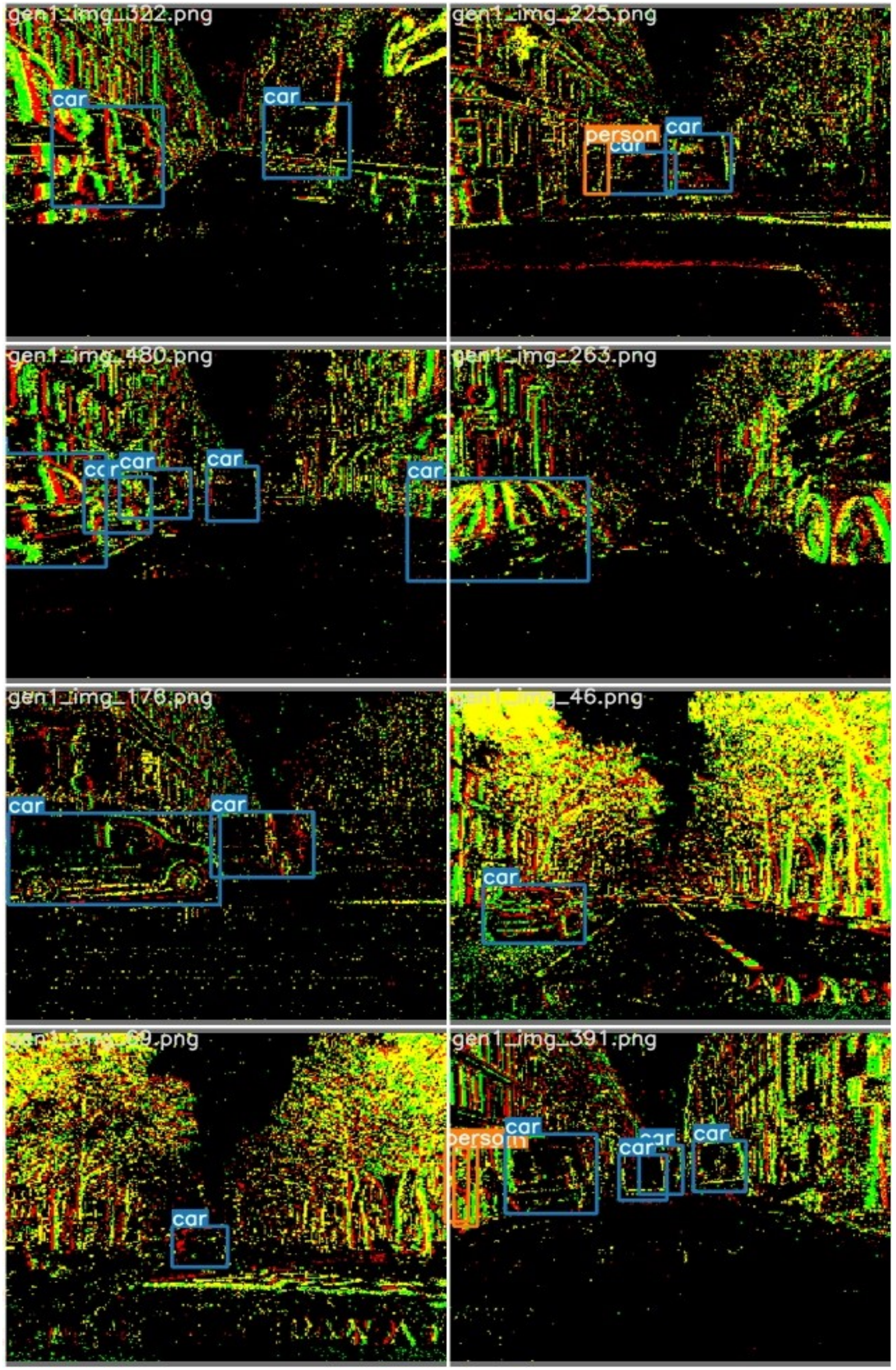
SNN for Object Detection: ANN-to-SNN Conversion



Limitations Currently Facing

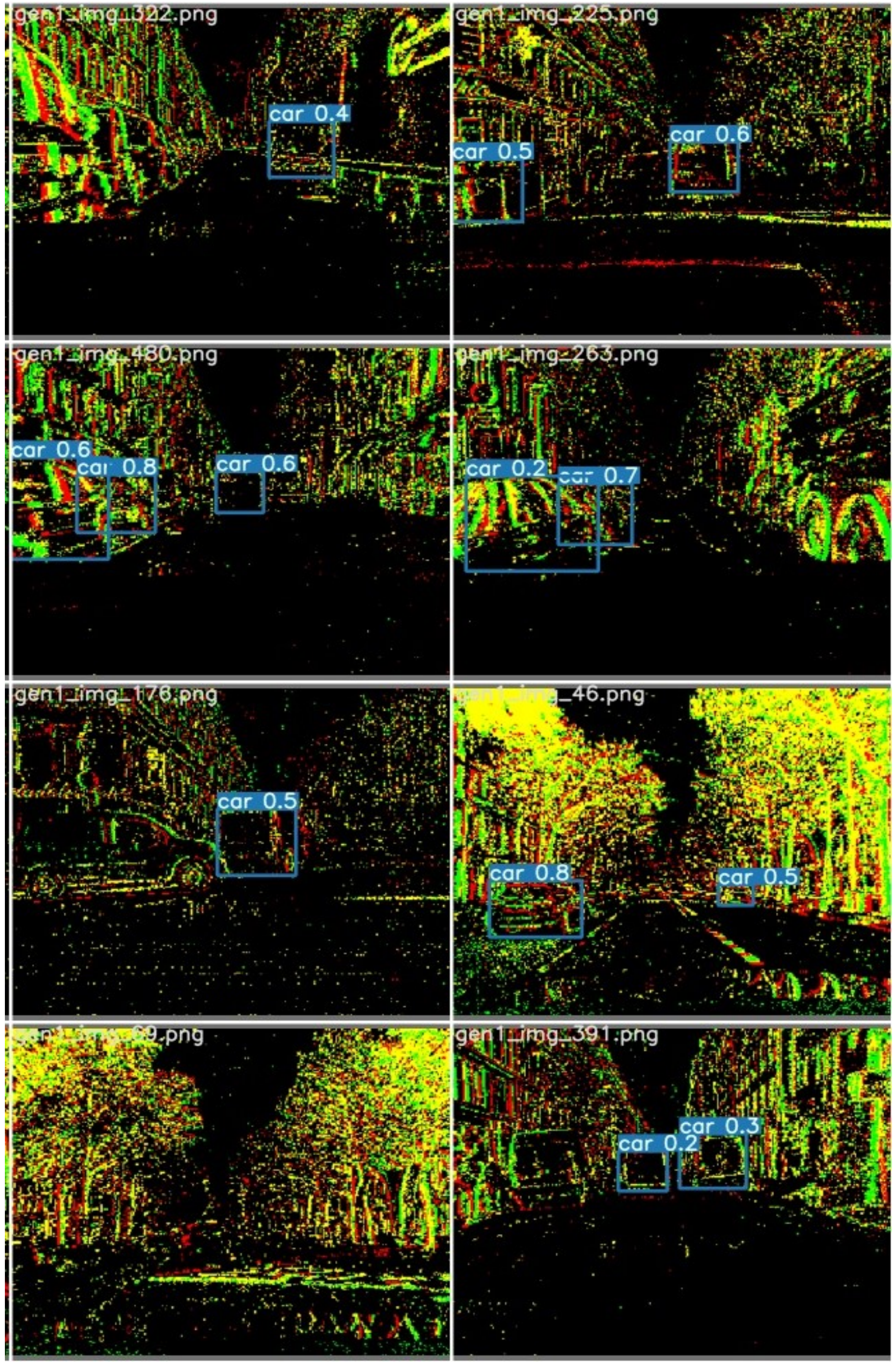
- Lack of RGB frames compatible with the event data to train the ANN.
- SNNs inherently perform very poorly in object detection tasks. (mAP@0.5 ~ 0.2)





Ground Truths

Predictions



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References

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