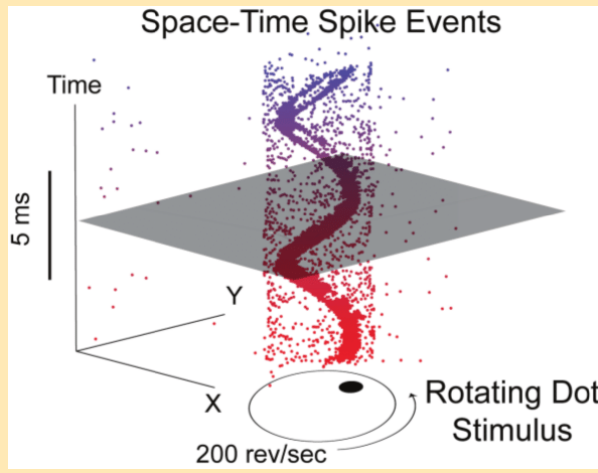


Performance comparison of DVS data downscaling methods using Spiking Neural Networks

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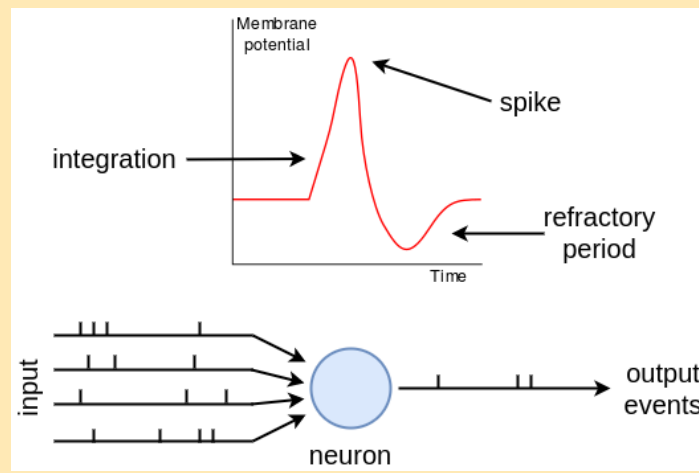
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Dynamic Vision Sensor



[Lichtsteiner, 2008] & [Mueggler, 2015]

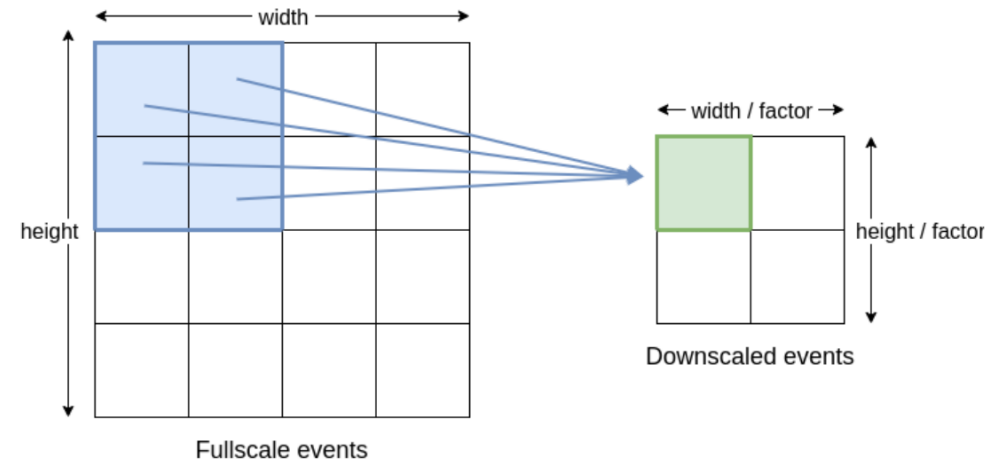
Spiking neural network



[Maas, 1997]

Combination DVS & SNN: compatibility of data types, information retention, energy efficiency and processing latency

Event data spatial downscaling



Existing methods

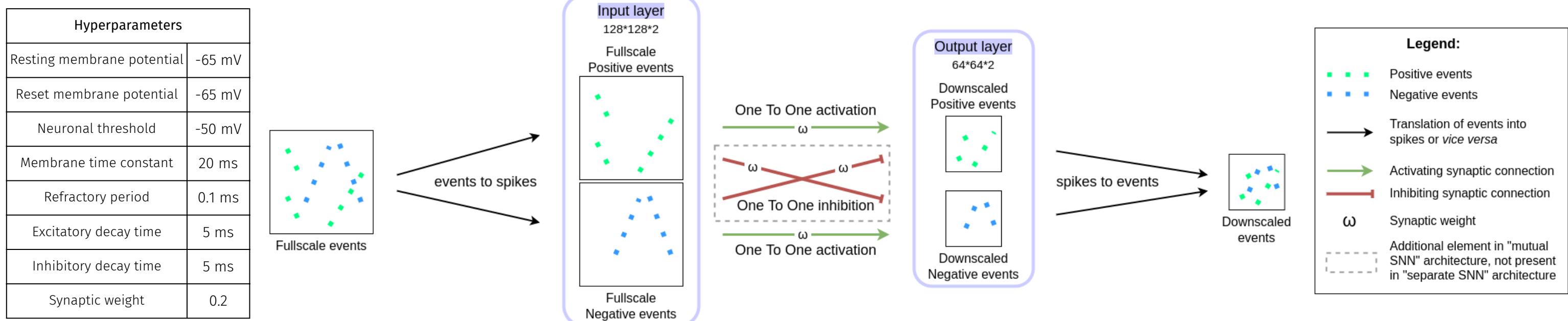
- [Lenz, 2021]
- [Gruel, 2022]
 - Spatial funnelling
 - Event count
 - Log luminance reconstruction

Why?

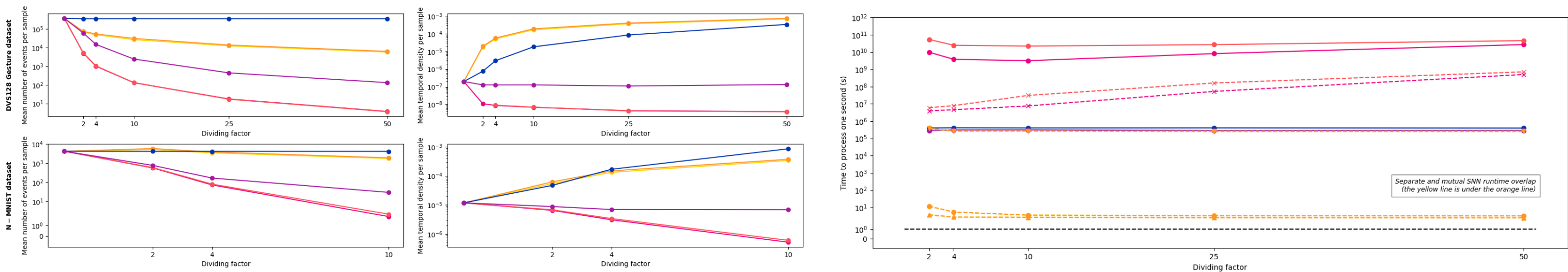
- difficult handling of heavy data by deep SNN models
- embedded systems' limitations in energy resources, memory, computational power and communication bandwidth
- energy consumption \propto number of spikes & input events \propto number of pixels

Our core objective: design a fully integrated energy-efficient SNN model able to run dynamically on a neuromorphic platform

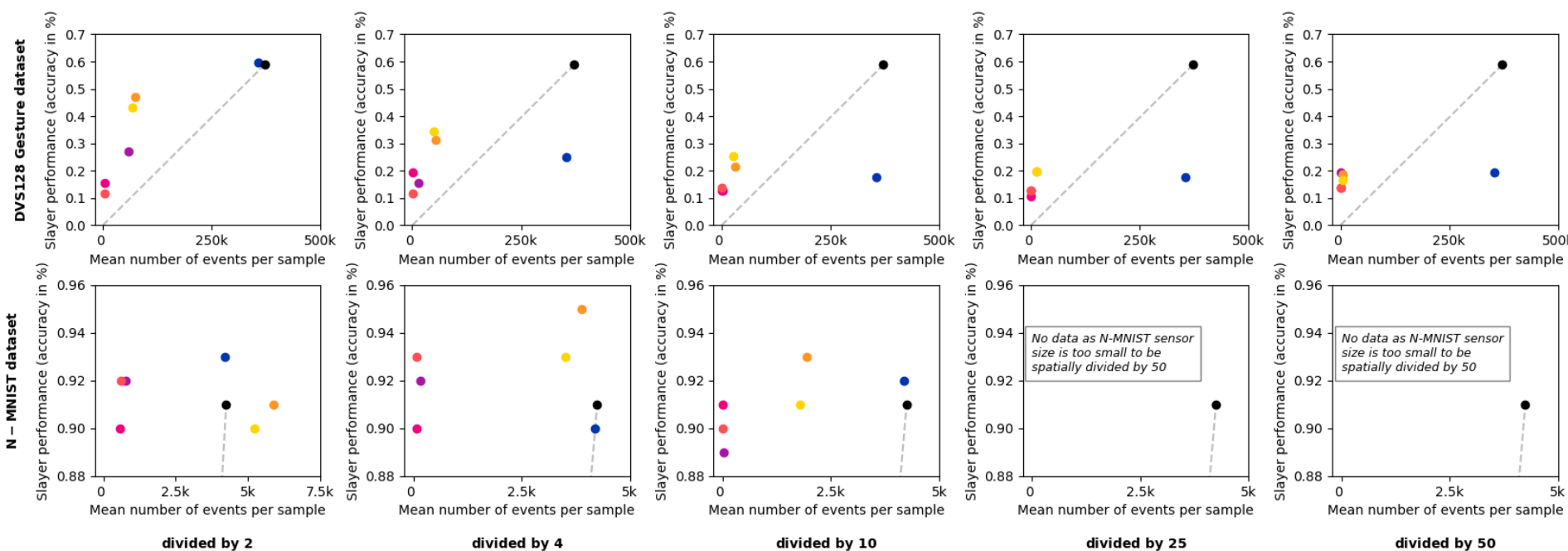
Our contribution: Event downscaling by SNN pooling



Quantitative and qualitative comparison



Comparison of physical properties and run time evolution for spatially downscaling 1 second of real time event data between different methods and dividers



Evolution of accuracy performance of the SLAYER classifier [Shrestha, 2018] between different methods and dividers

- Spatial funnelling
- Event count
- Linear log luminance - extrapolation
- Linear log luminance - constant
- Cubic log luminance - extrapolation
- Cubic log luminance - constant
- Mutual SNN - accumulated over 1 ms
- Mutual SNN - accumulated over 1 s
- Mutual SNN - no temporal accumulation
- Separate SNN - accumulated over 1 ms
- Separate SNN - accumulated over 1 s
- Separate SNN - no temporal accumulation

Quantitative and qualitative assessment of the different event spatial downscaling methods on two datasets: N-MNIST [Orchard, 2015] and DVS 128 Gesture [Amir, 2017]

SNN pooling achieves an efficient trade-off between the optimisation of physical properties, classification performance, real-time data handling and energy consumption

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