UNIVERSITÄT ZU LÜBECK

BASLER

Artificial Intelligence for Processing of Event-Based Vision Sensor Data

Steffen Hagedorn | 29.09.2022

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B.Sc. **Medizinische Ingenieurwissenschaften**
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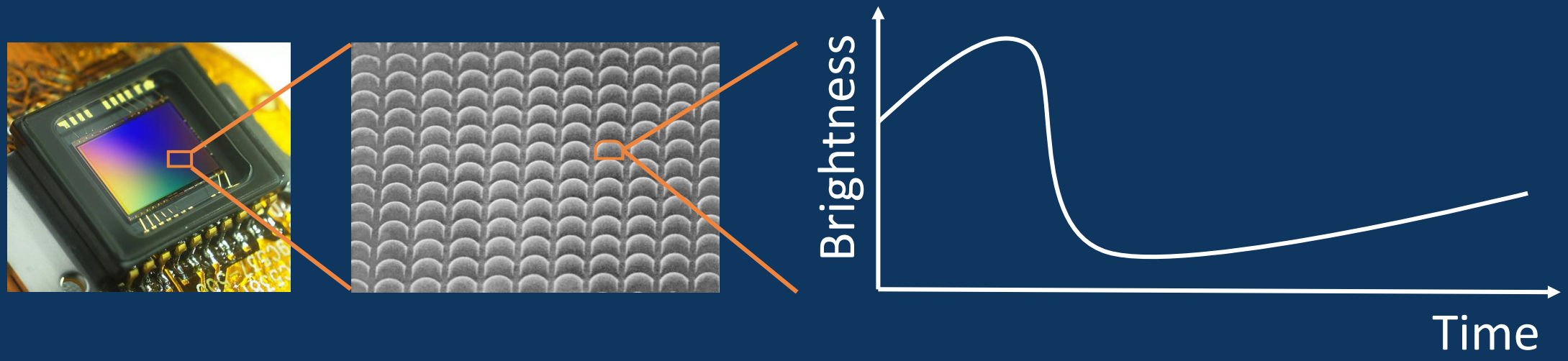
Lübeck, Oslo

Ph.D. **Perception for Autonomous Driving**
Stuttgart

What is Event-Based Vision?



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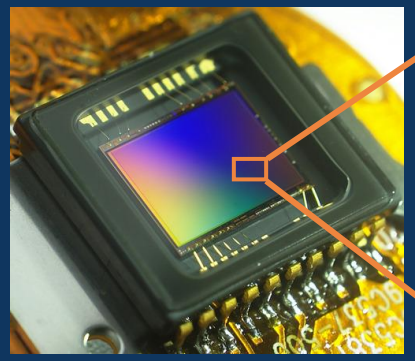

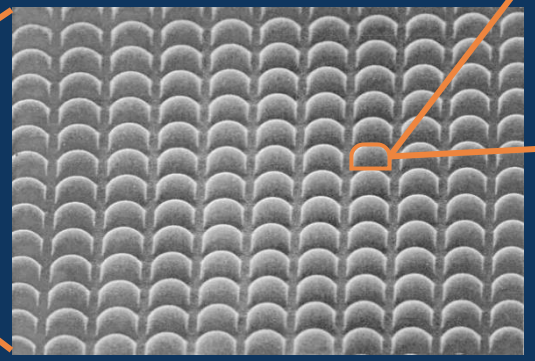

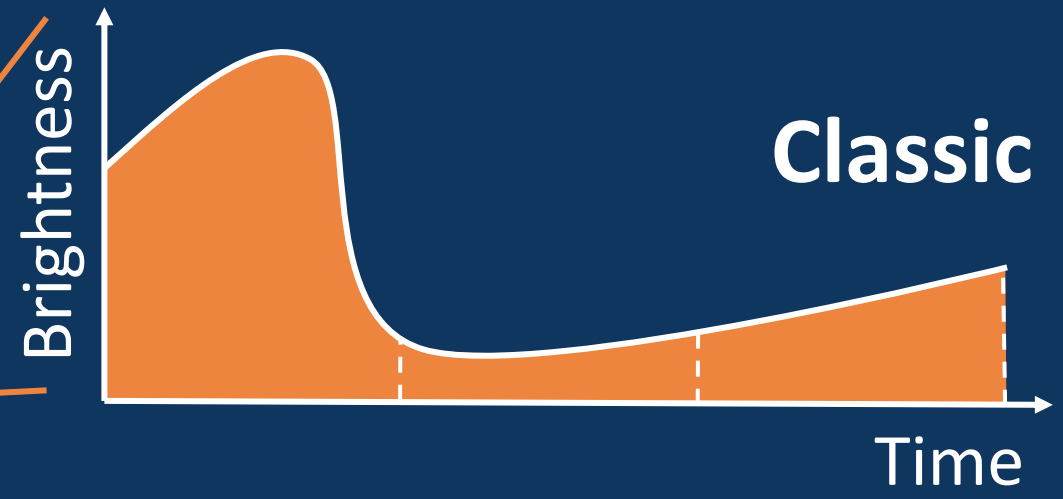

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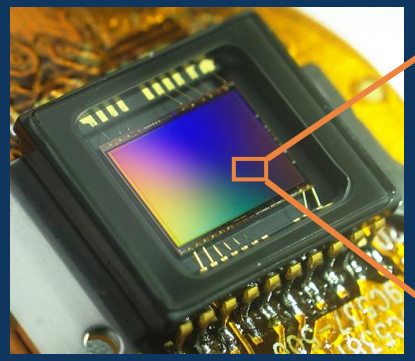
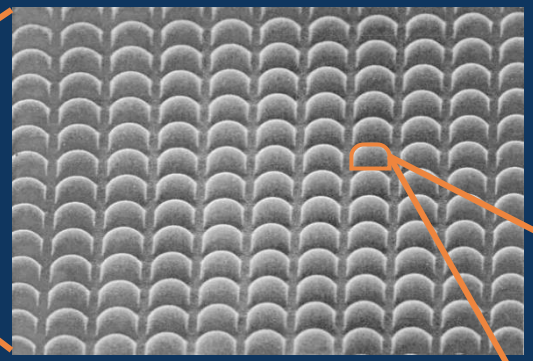
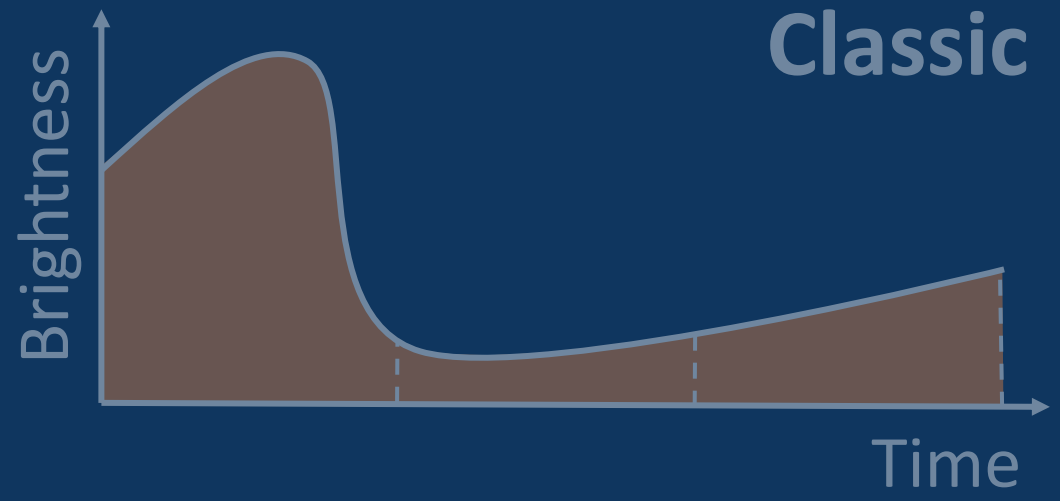
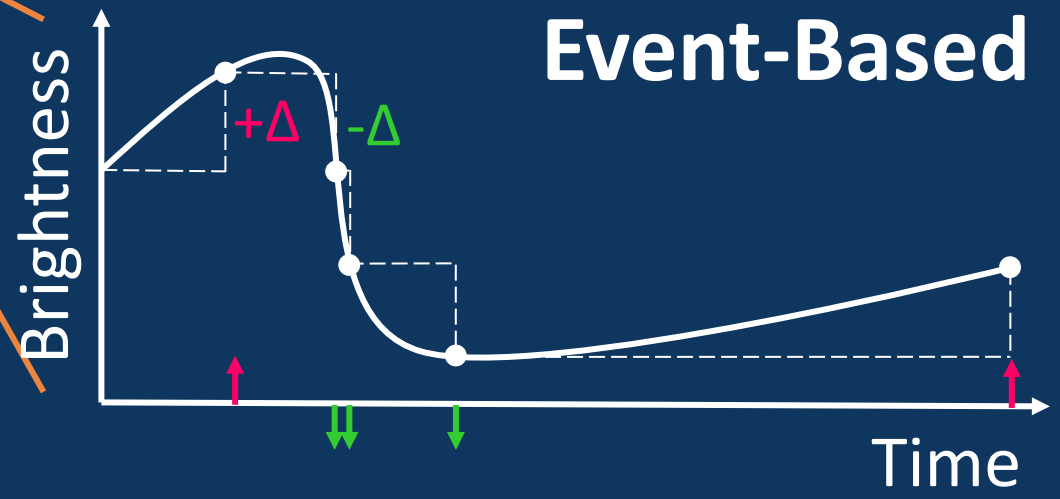






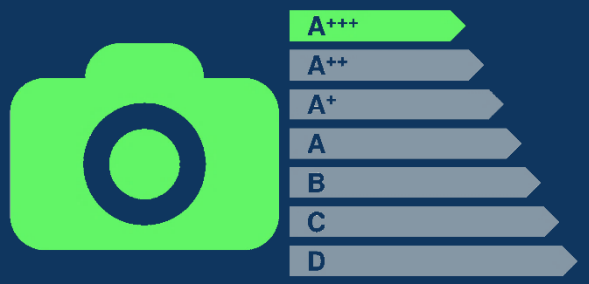


[1]

Advantages

Low

Data Output



Energy Use

High

Dynamic Range

Time Resolution

Problem

State of the Art

Concept

Results

Insights

Problem

State of the Art

Concept

Results

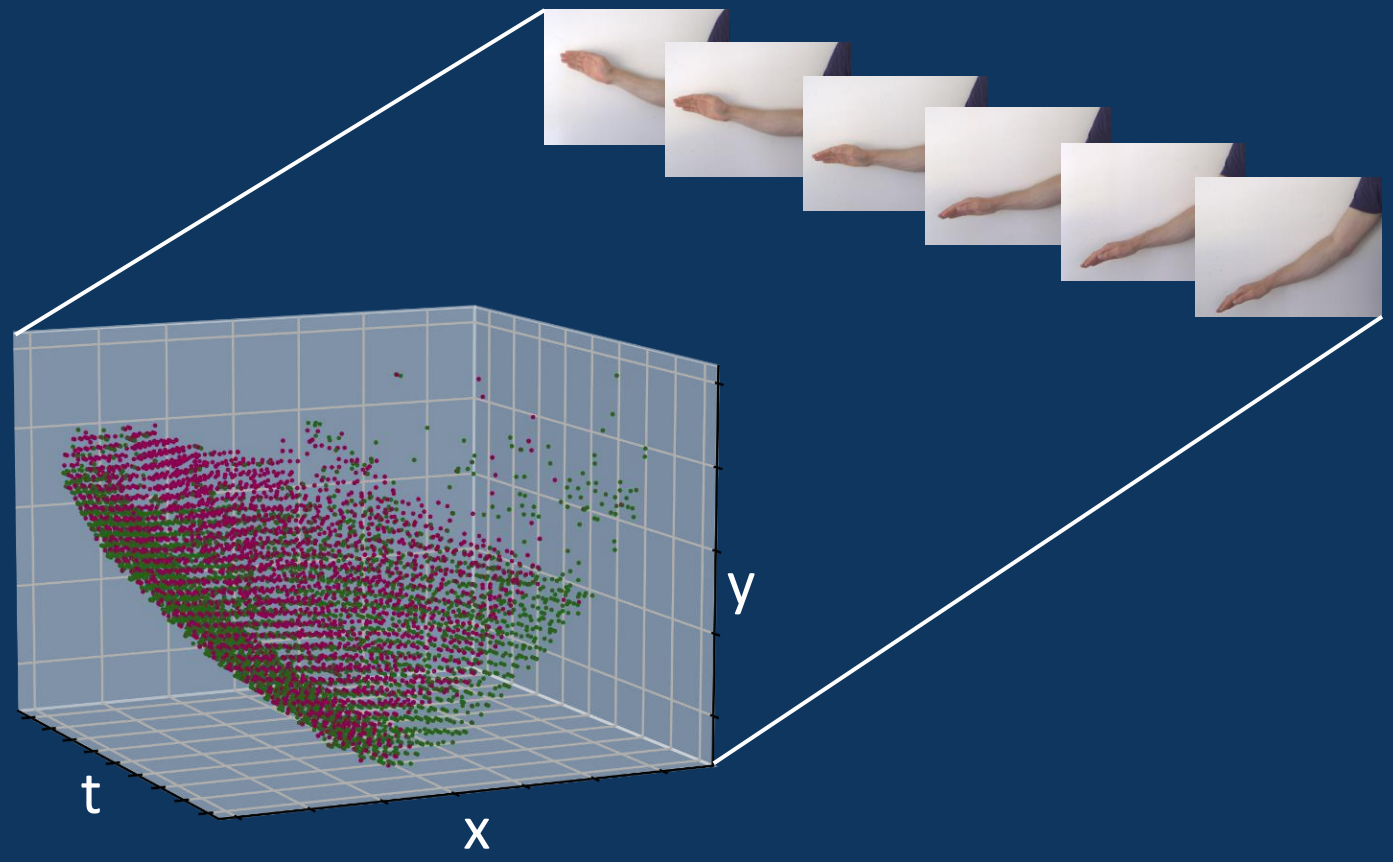
Insights

Event Data ≠ Image Data

- Classic image processing not applicable
- ~~Huge effort to develop new methods~~

→ Use AI!

- **Existing solutions don‘t use properties of event data**



Research Questions

- How does **current AI** process event data?
- **Requirements** for processing that suits event data?
- **Develop model** according to requirements

Problem

State of the Art

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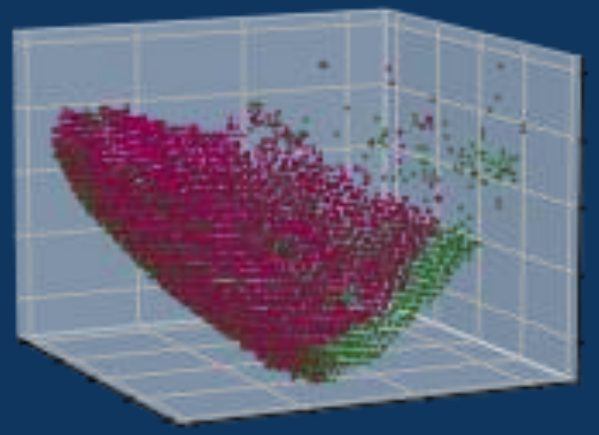
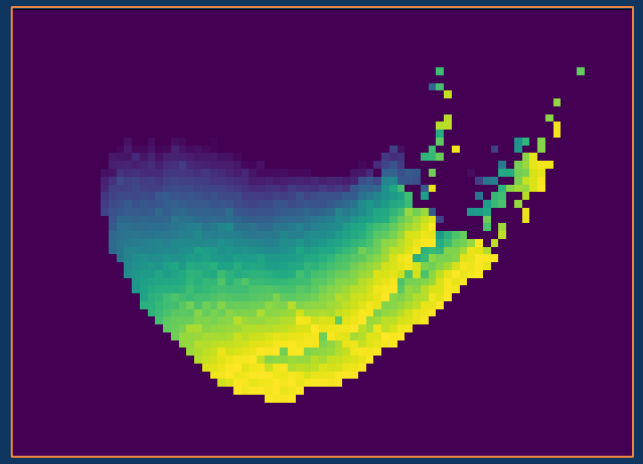
Results

Insights

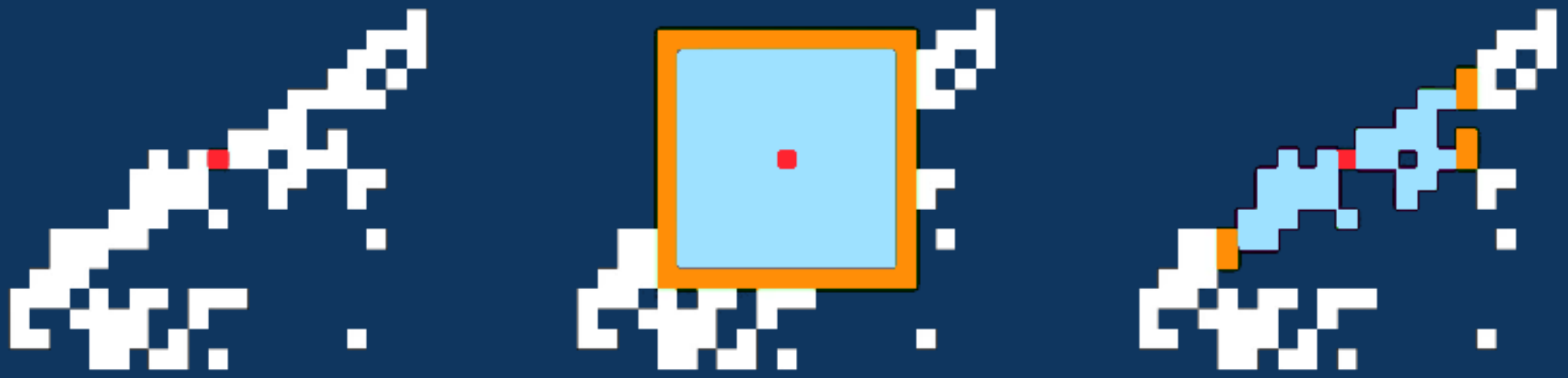
CNN on 2D Representation [3]





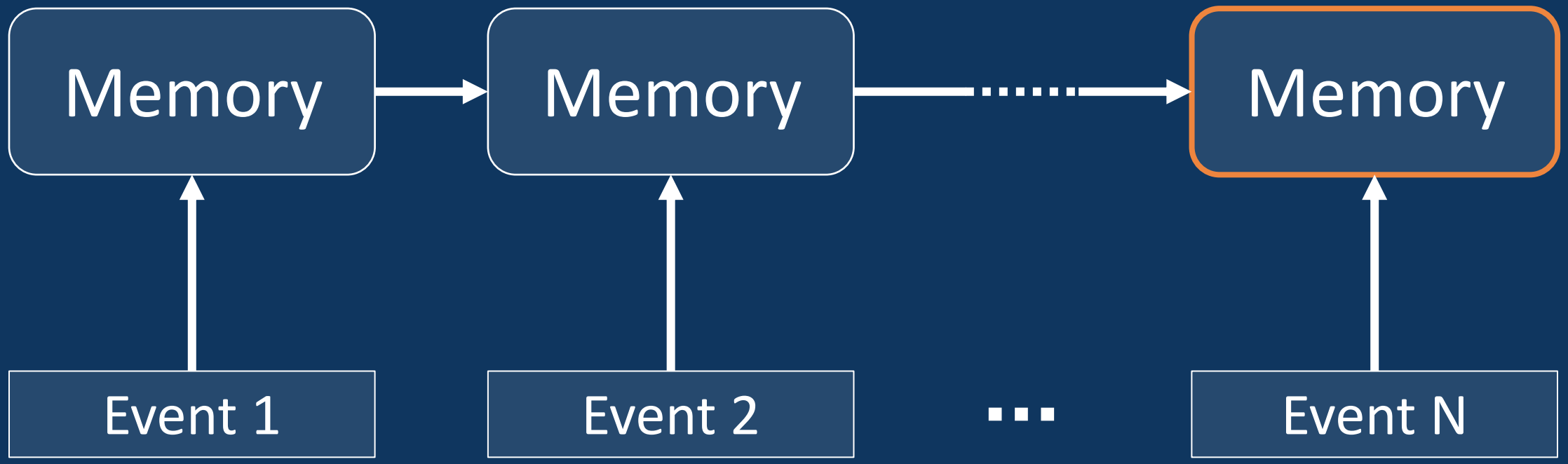
CNN

Sparse CNN

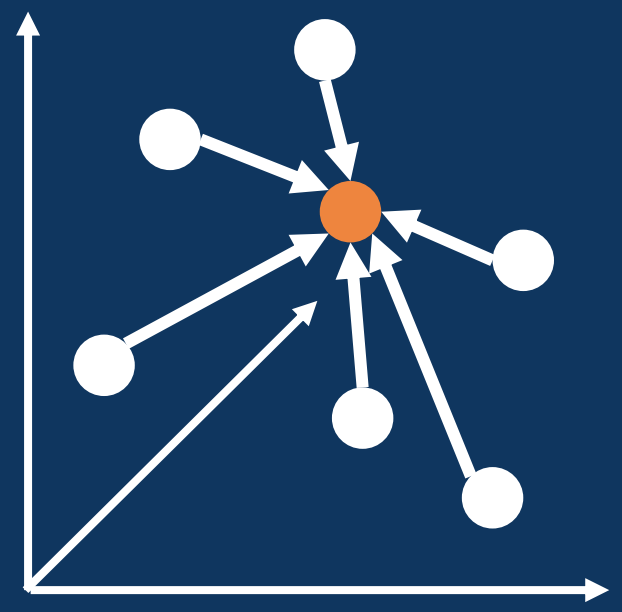


New Event | Conv | Sparse Conv [4]

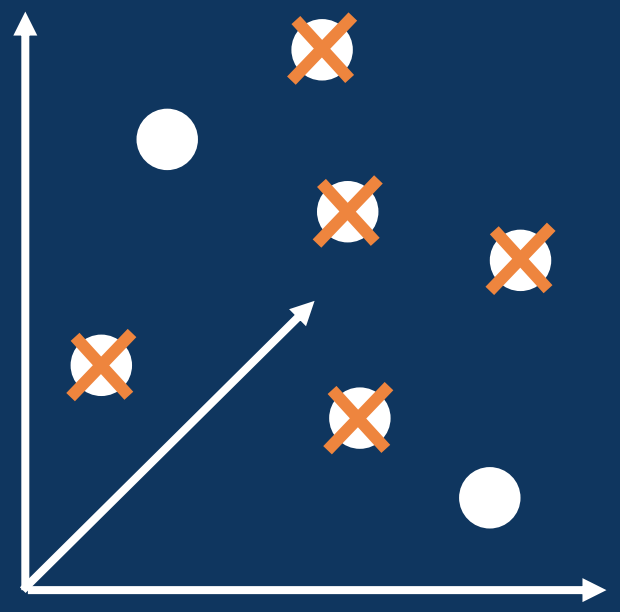
Sequence Processing



3D Processing [6]



Aggregate Information



Reduce

Research Questions

- How does **current AI** process event data?
  - CNN on 2D Representation
  - Sparse CNN
  - Sequence Processing
  - 3D Processing
- **Requirements** for processing that suits event data?
- **Develop model** according to requirements

Problem

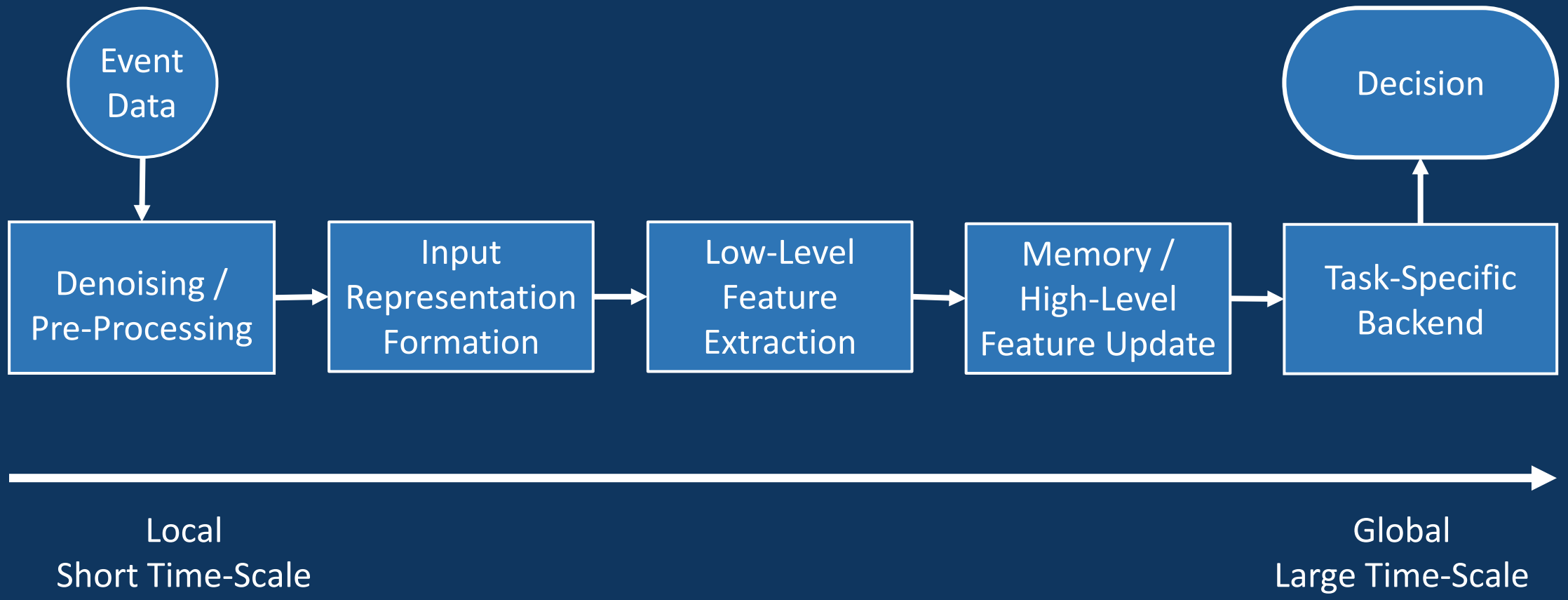
State of the Art

Concept

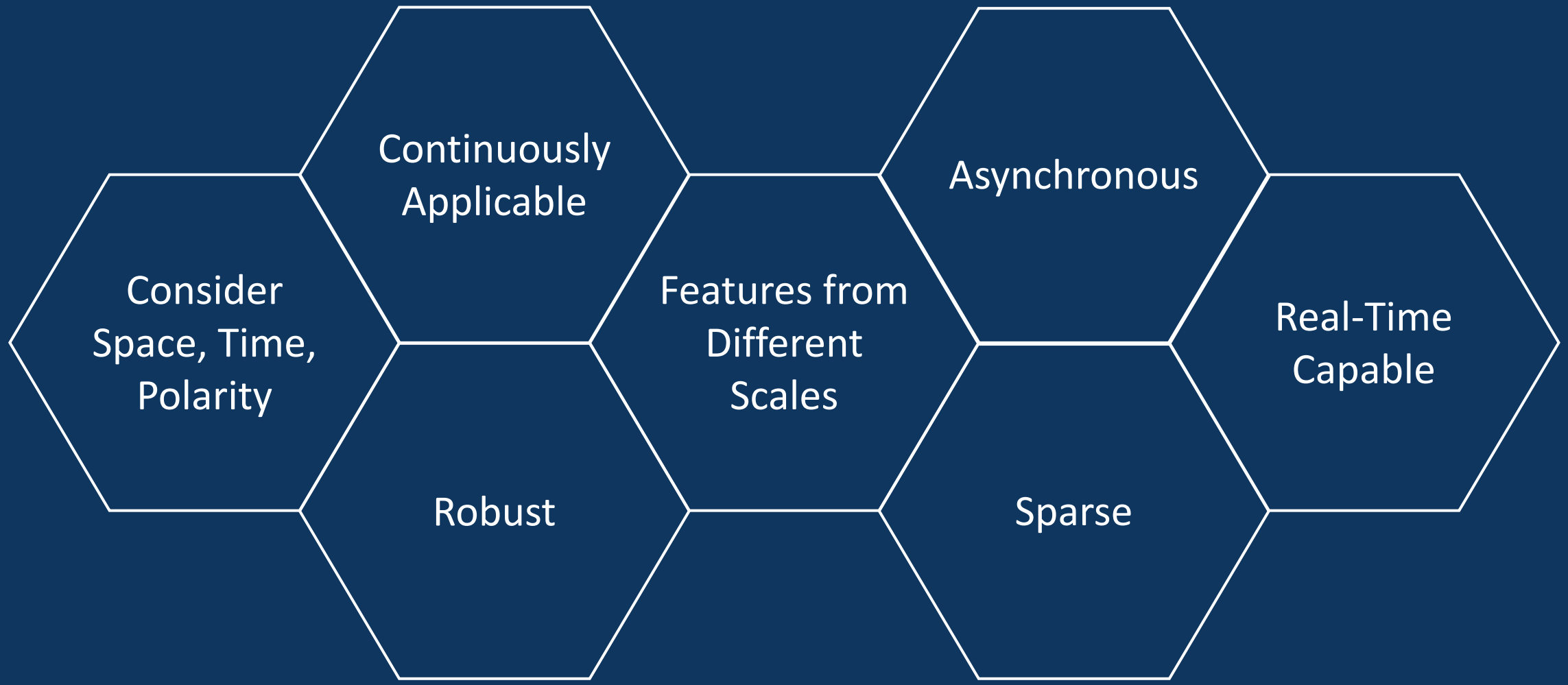
Results

Insights

Processing Model

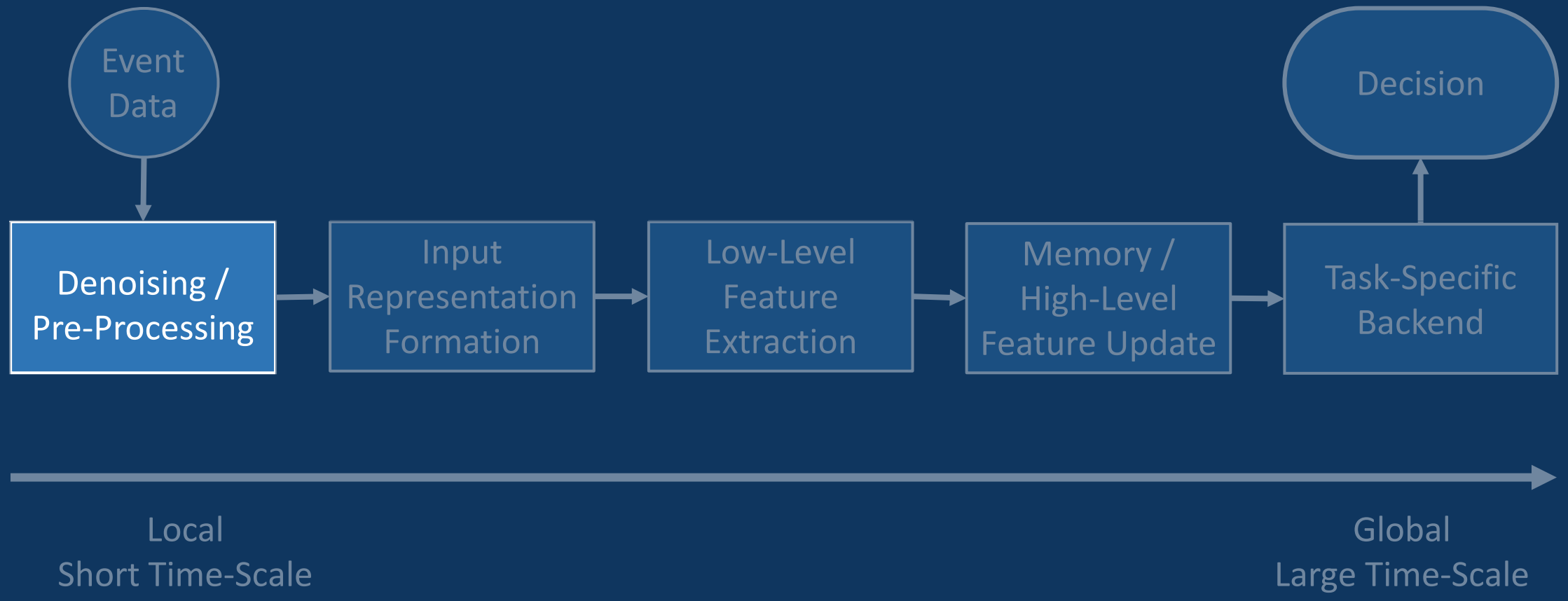


Requirements

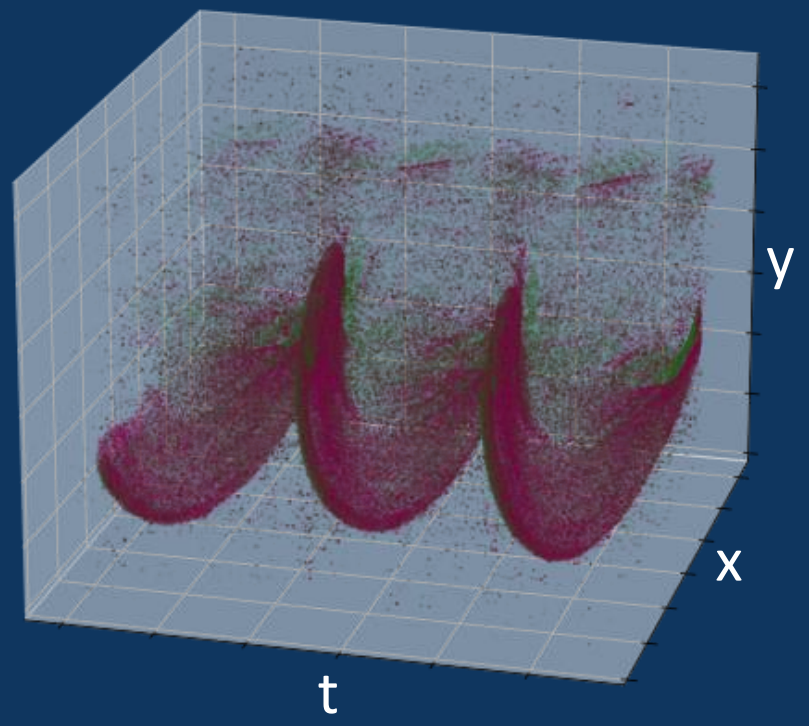


Research Questions

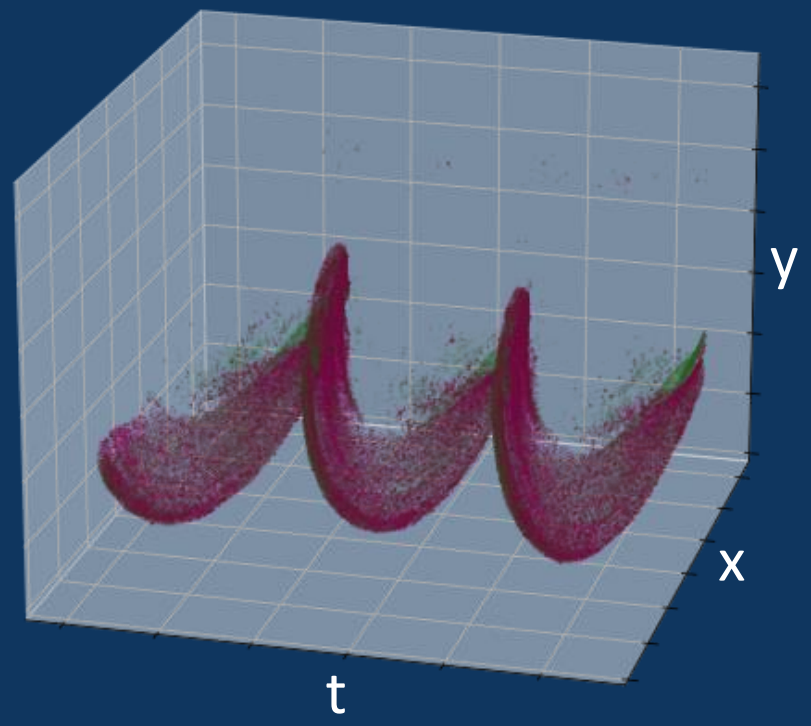
- How does **current AI** process event data?
- **Requirements** for processing that suits event data?
- **Develop model** according to requirements

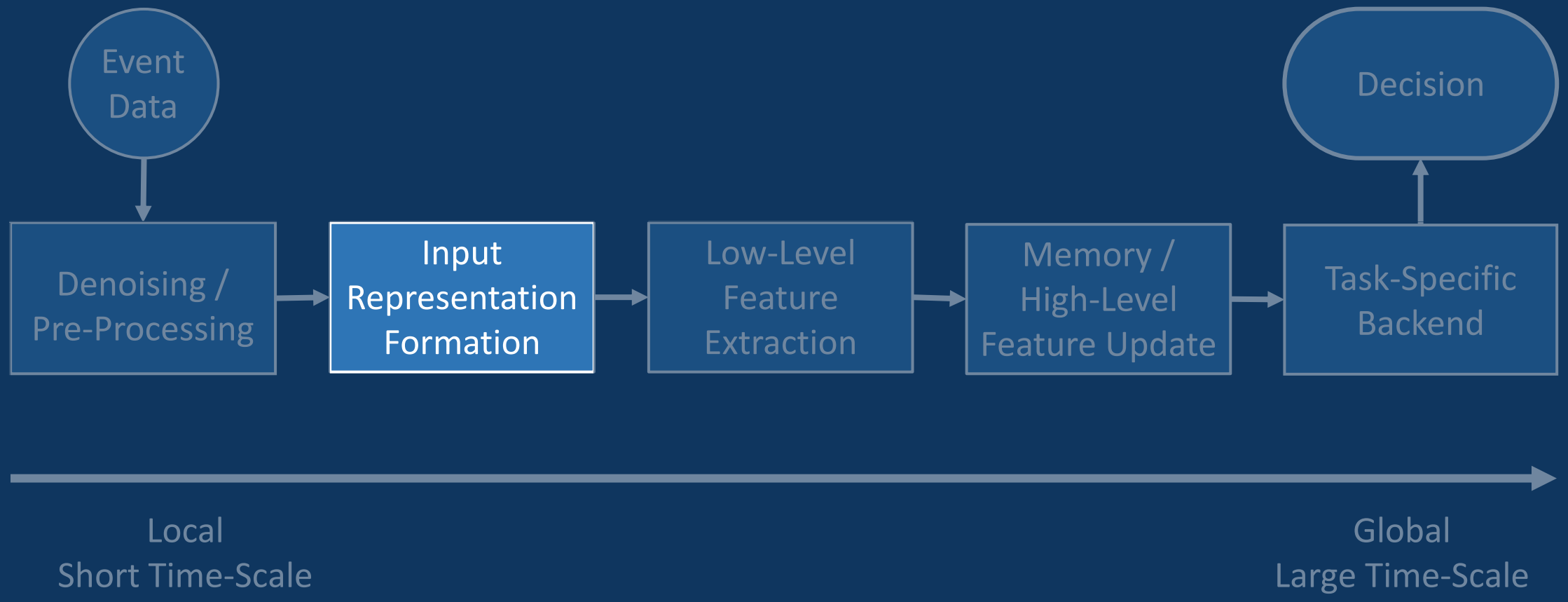

Event Data
Decision
Denoising / Pre-Processing
Input Representation Formation
Low-Level Feature Extraction
Memory / High-Level Feature Update
Task-Specific Backend
Local
Short Time-Scale
Global
Large Time-Scale

Denoising



Spatio-Temporal Correlation Filter (STCF) [7]

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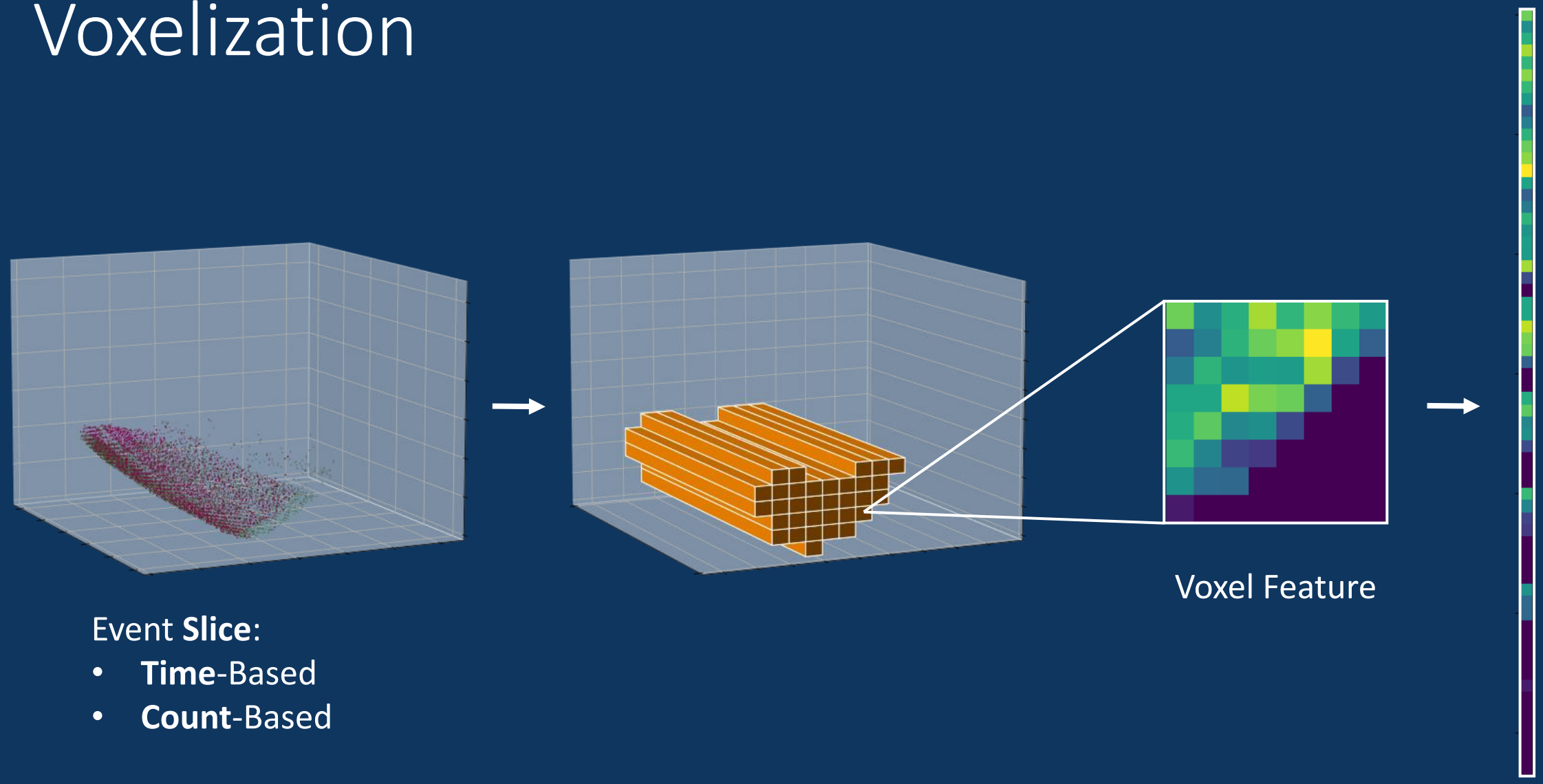
Task-Specific Backend
Local
Short Time-Scale
Global
Large Time-Scale

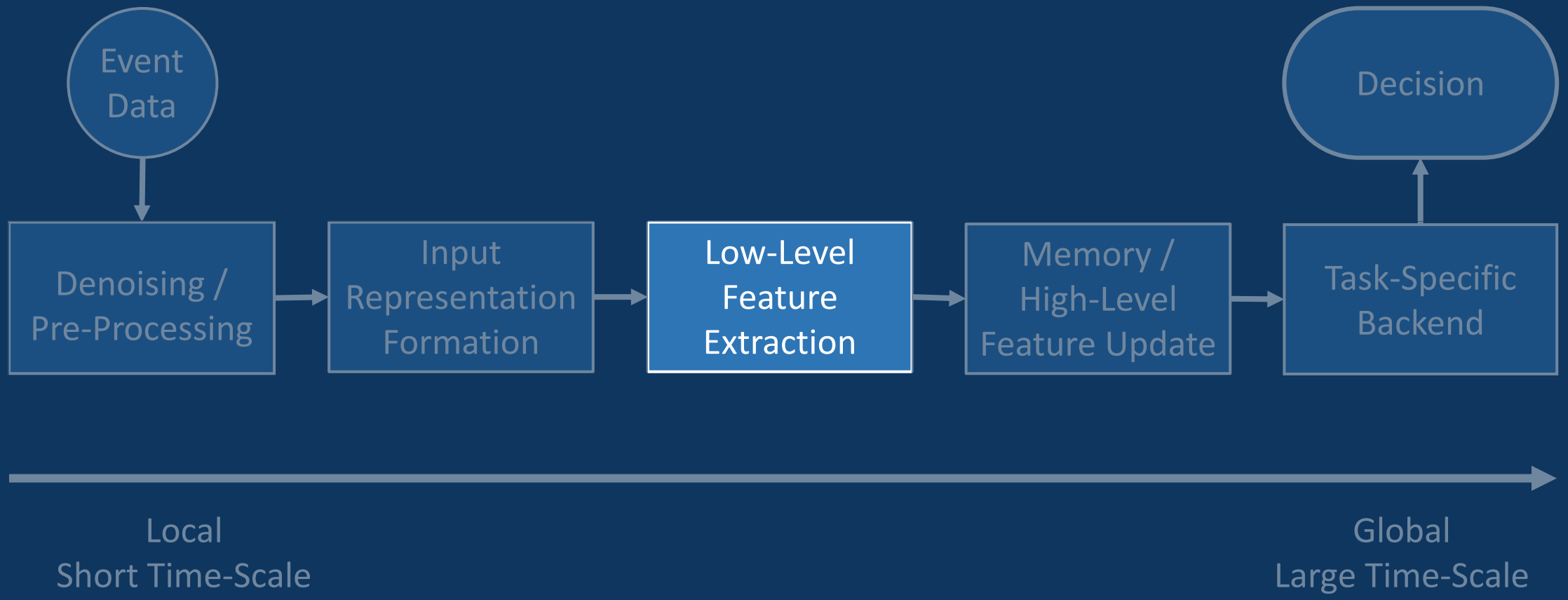
Voxelization



Event **Slice**:

- **Time**-Based
- **Count**-Based

[8]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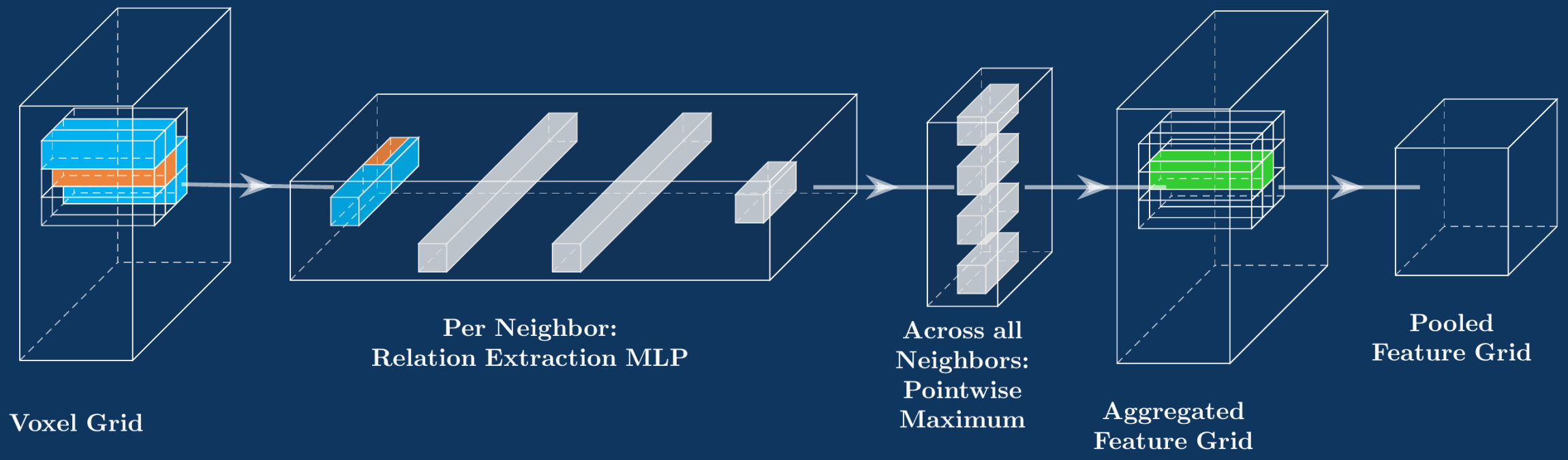
Aggregate-Pool



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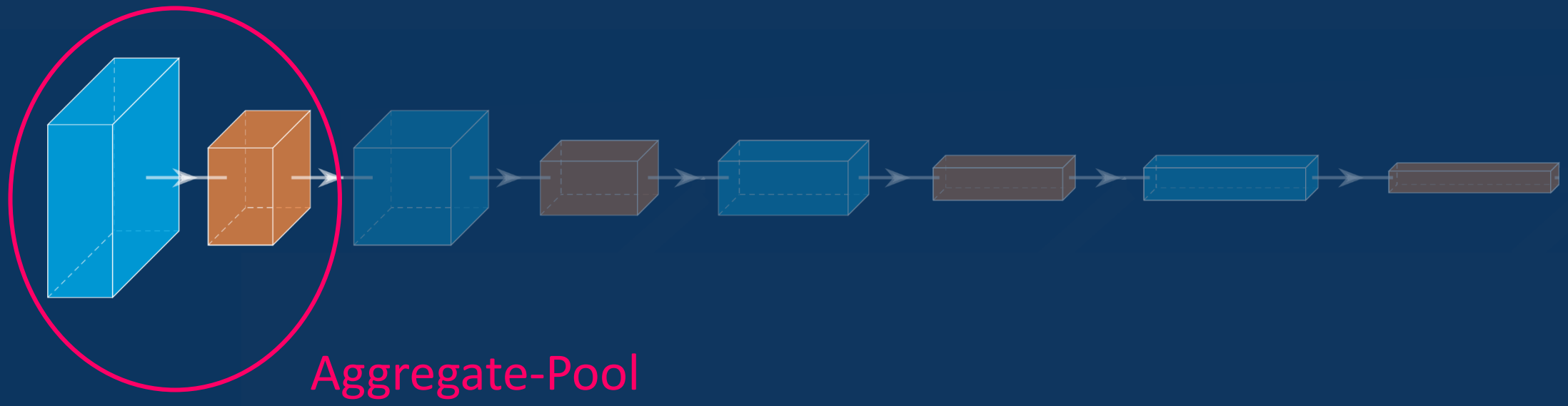

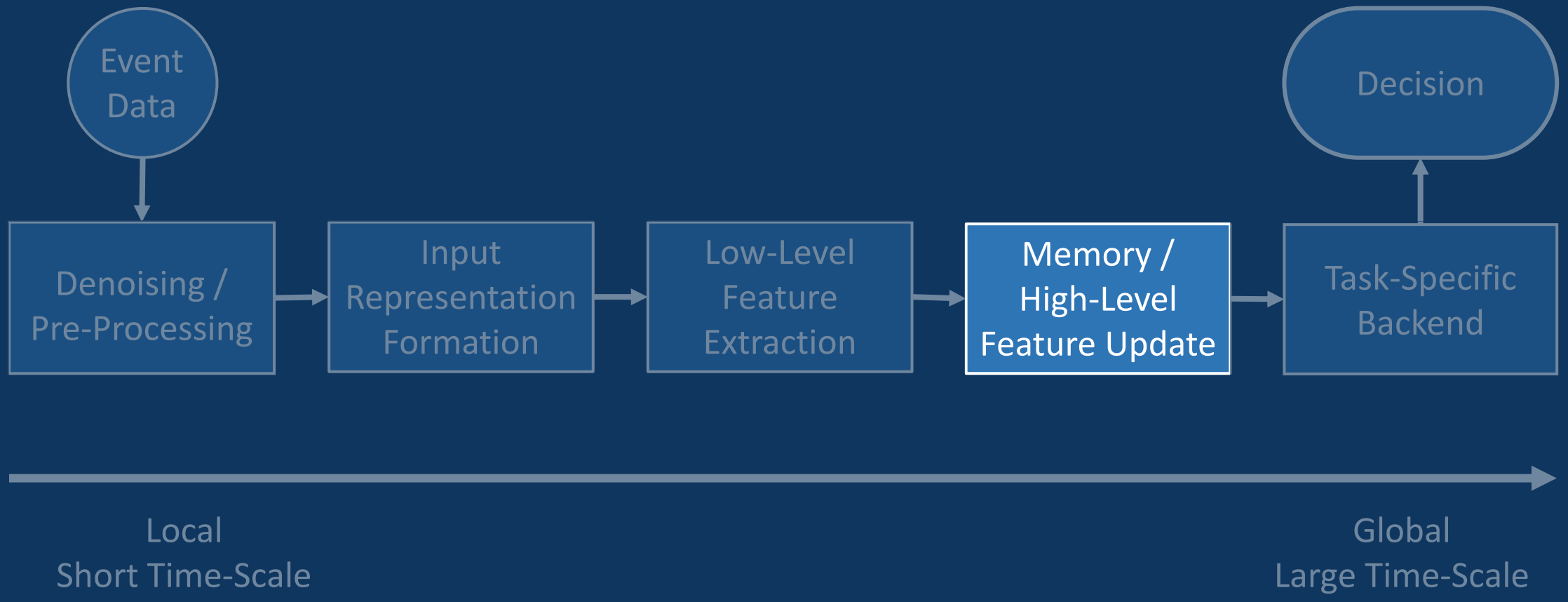
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Low-Level Feature Extraction
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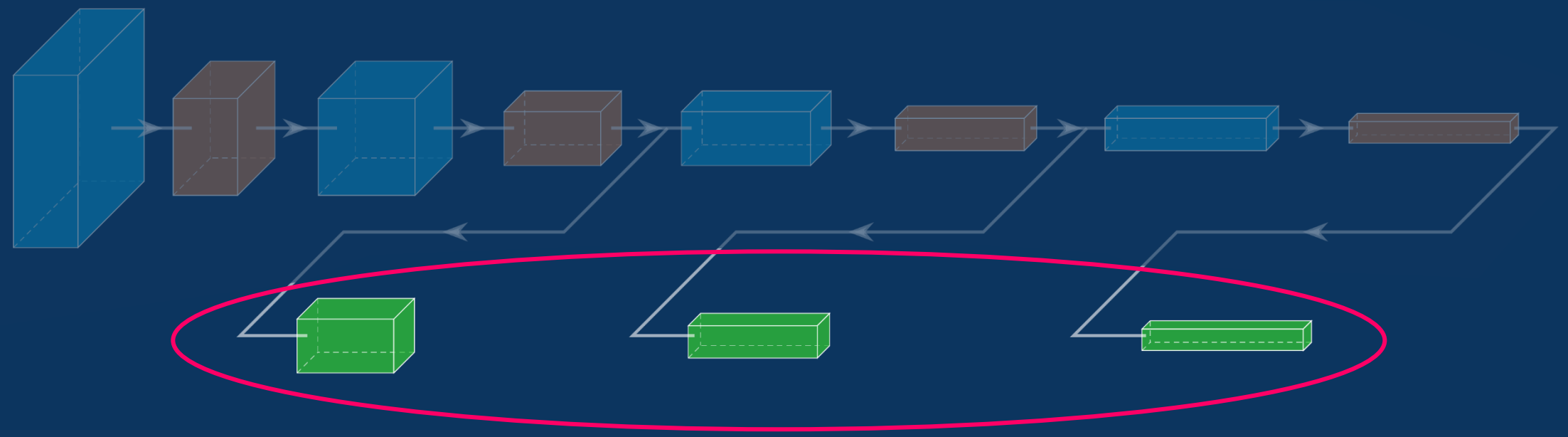
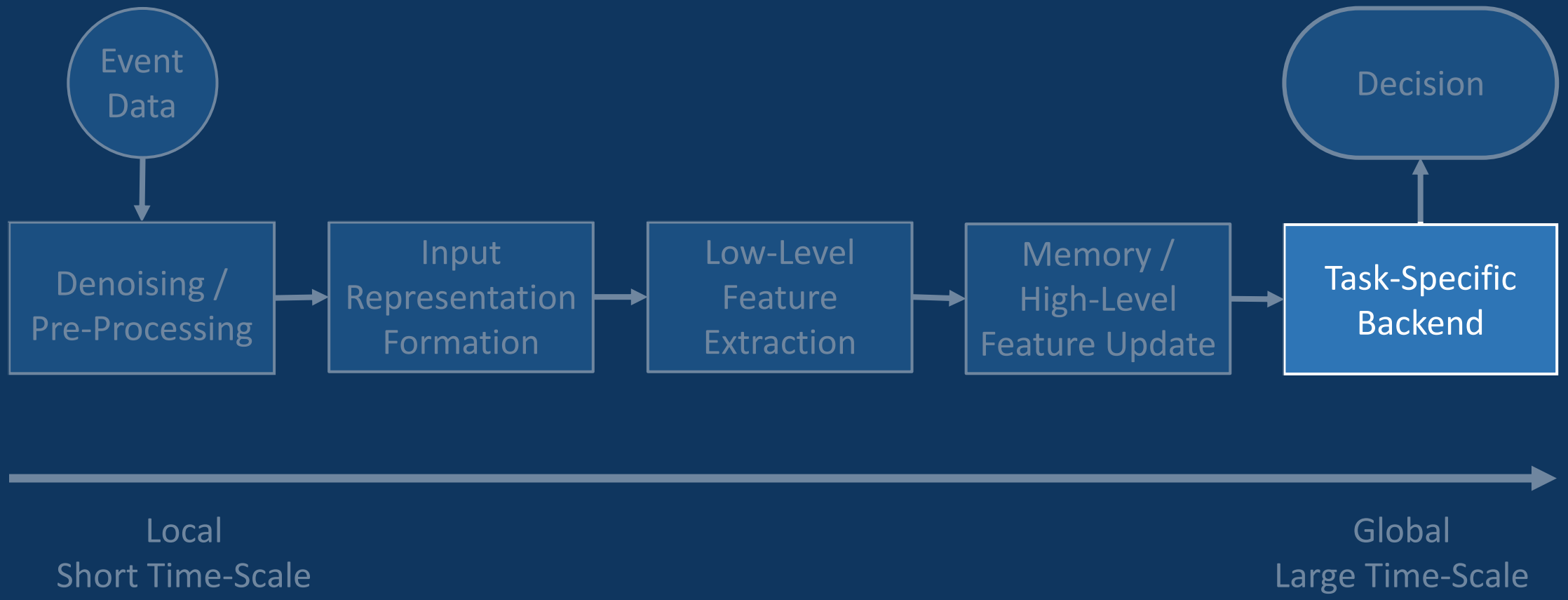
Global
Large Time-Scale

High-Level Memory



LSTM [9]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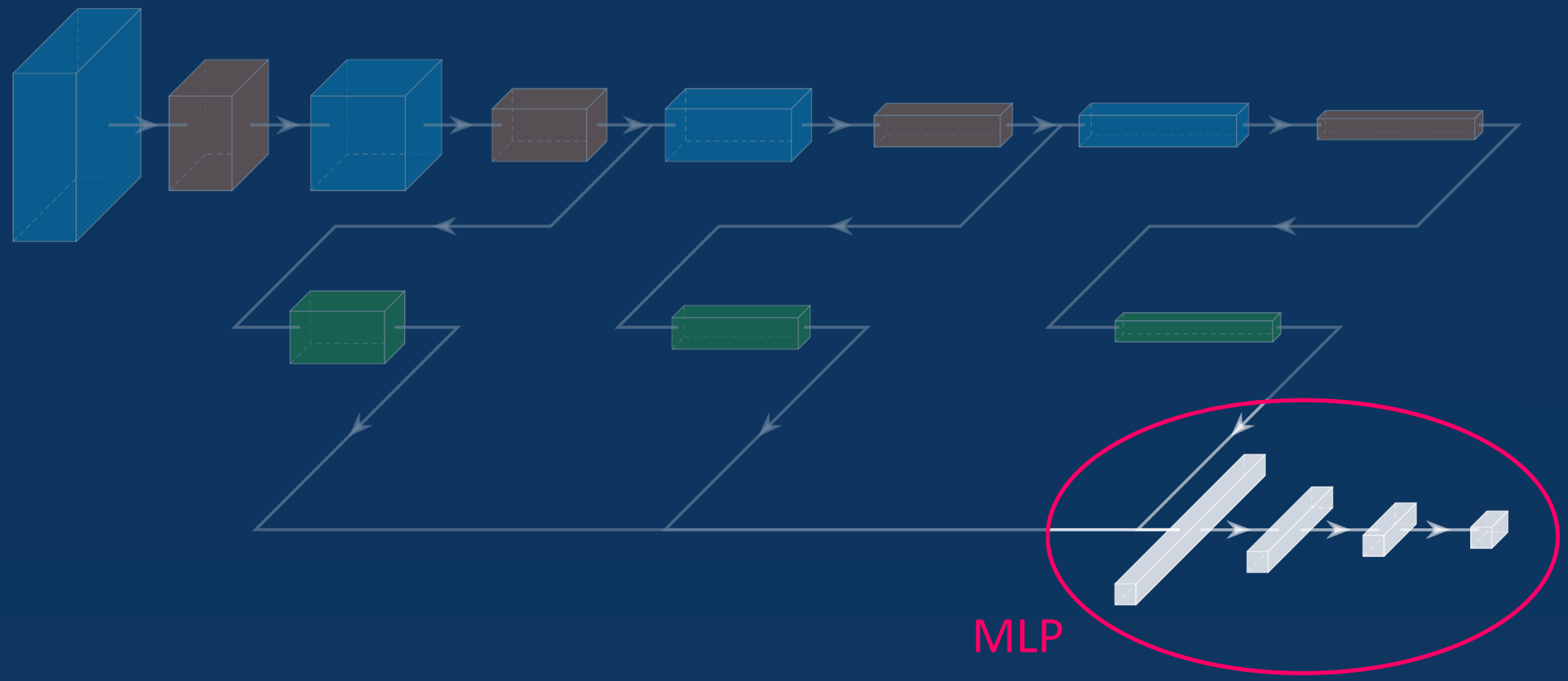
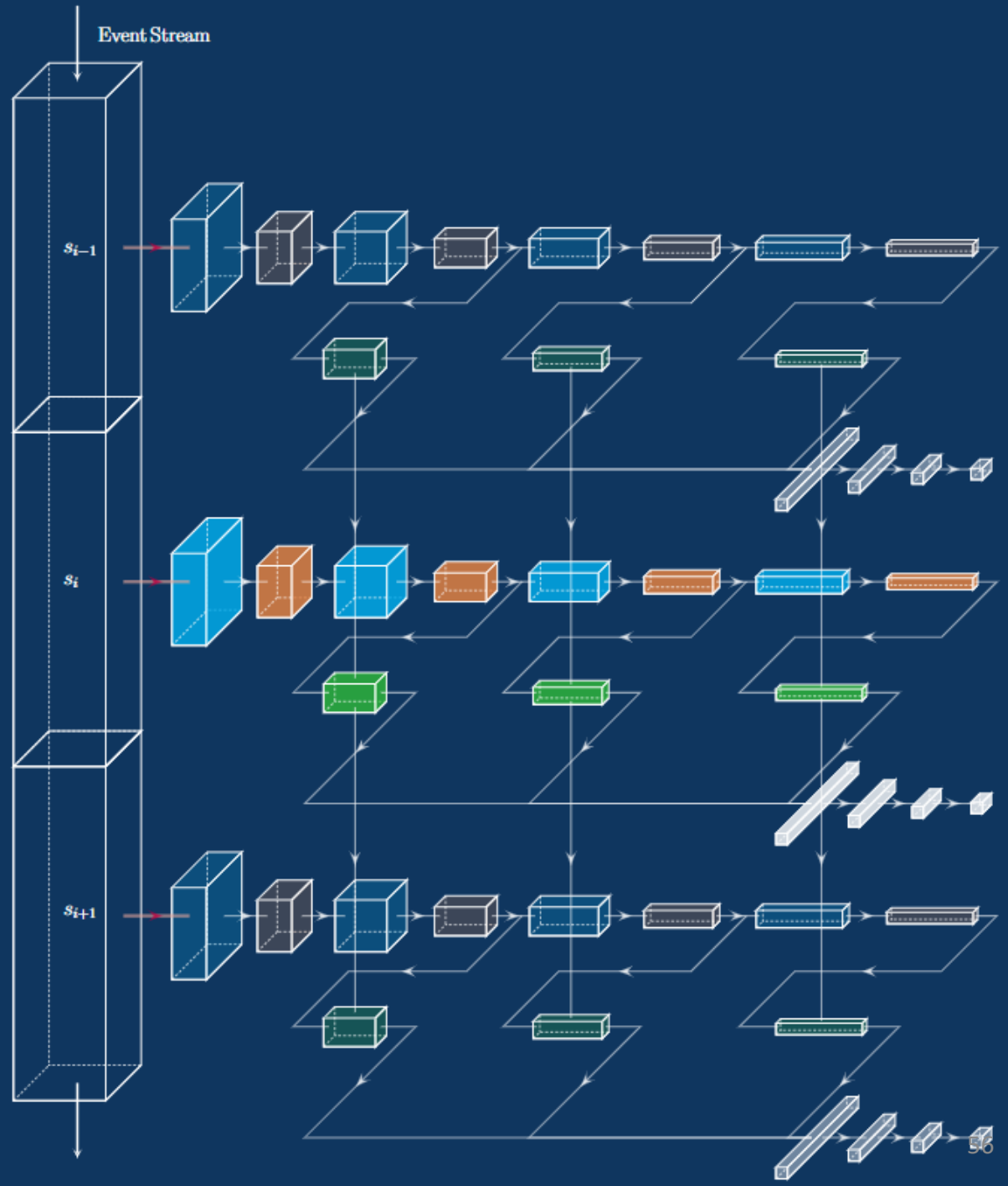
Backend

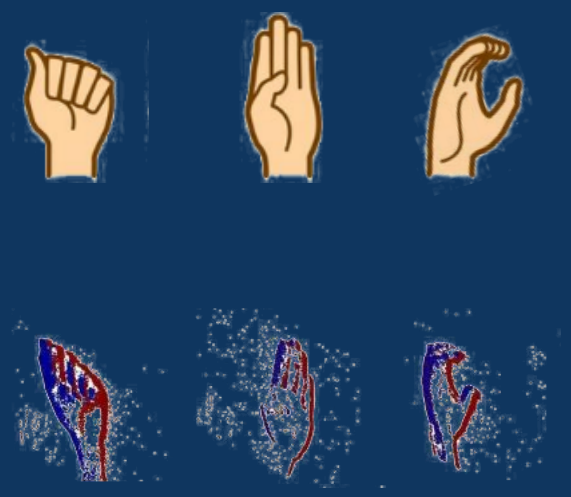


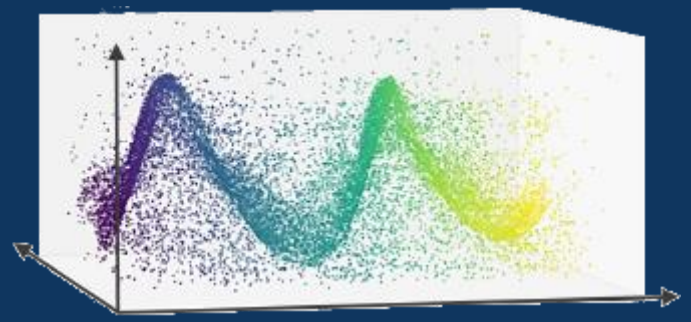
HAREM Net

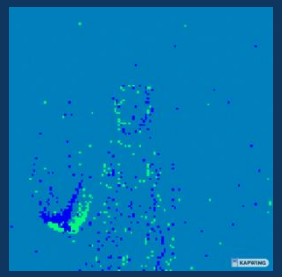
Hierarchically **A**ggregated **R**ecursive **E**vent **M**emory **Net**work

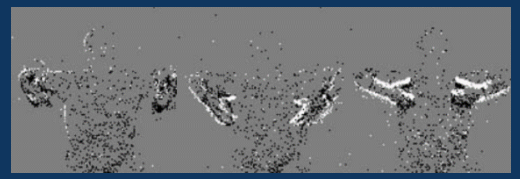


Gesture Classification









ASL DVS
Alphabet

DVS 128 Gesture
Smart Device Control

SL Animals DVS
Animal Gestures

[12]

Easy → Hard

Problem

State of the Art

Concept

Results

Insights

Accuracy

Model	Accuracy [%]	
	ASL DVS	
SLAYER		
STBP		
GCNN	90.1	
EventNet	83.33	
PointNet++		
Timestamp CNN		
DGCNN		
Matrix LSTM	99.73	21.43 M parameters
EV-VGCNN	98.3	
HAREM Net	**98.1**	8.8 M parameters

Accuracy

Model	Accuracy [%]	
	ASL DVS	
SLAYER		
STBP		
GCNN	90.1	
EventNet	83.33	
PointNet++		
Timestamp CNN		
DGCNN		
Matrix LSTM	99.73	
EV-VGCNN	98.3	not continuously applicable
HAREM Net	**98.1**	continuously applicable

Accuracy

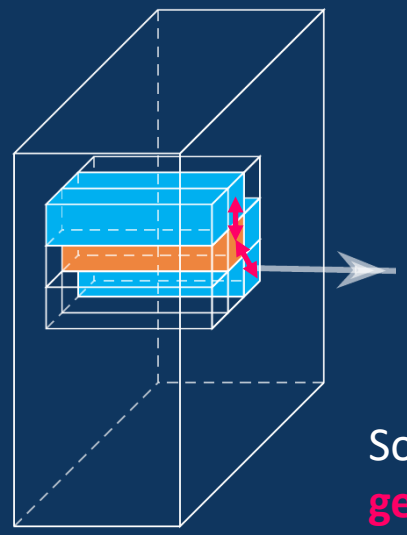
Model	Accuracy [%]	
	ASL DVS	DVS 128 Gesture
SLAYER		93.64
STBP		
GCNN	90.1	
EventNet	83.33	
PointNet++		97.08
Timestamp CNN		97.35
DGCNN		98.56
Matrix LSTM	99.73	
EV-VGCNN	98.3	
HAREM Net	**98.1**	**88.5**

Δ = -10 %

Accuracy

Model	Accuracy [%]	
	ASL DVS	DVS 128 Gesture
SLAYER		93.64
STBP		
GCNN	90.1	
EventNet	83.33	
PointNet++		97.08
Timestamp CNN		97.35
DGCNN		98.56
Matrix LSTM	99.73	
EV-VGCNN	98.3	
HAREM Net	**98.1**	**88.5**

Δ = -10 %



Solution: Consider **geometric relation** in aggregation

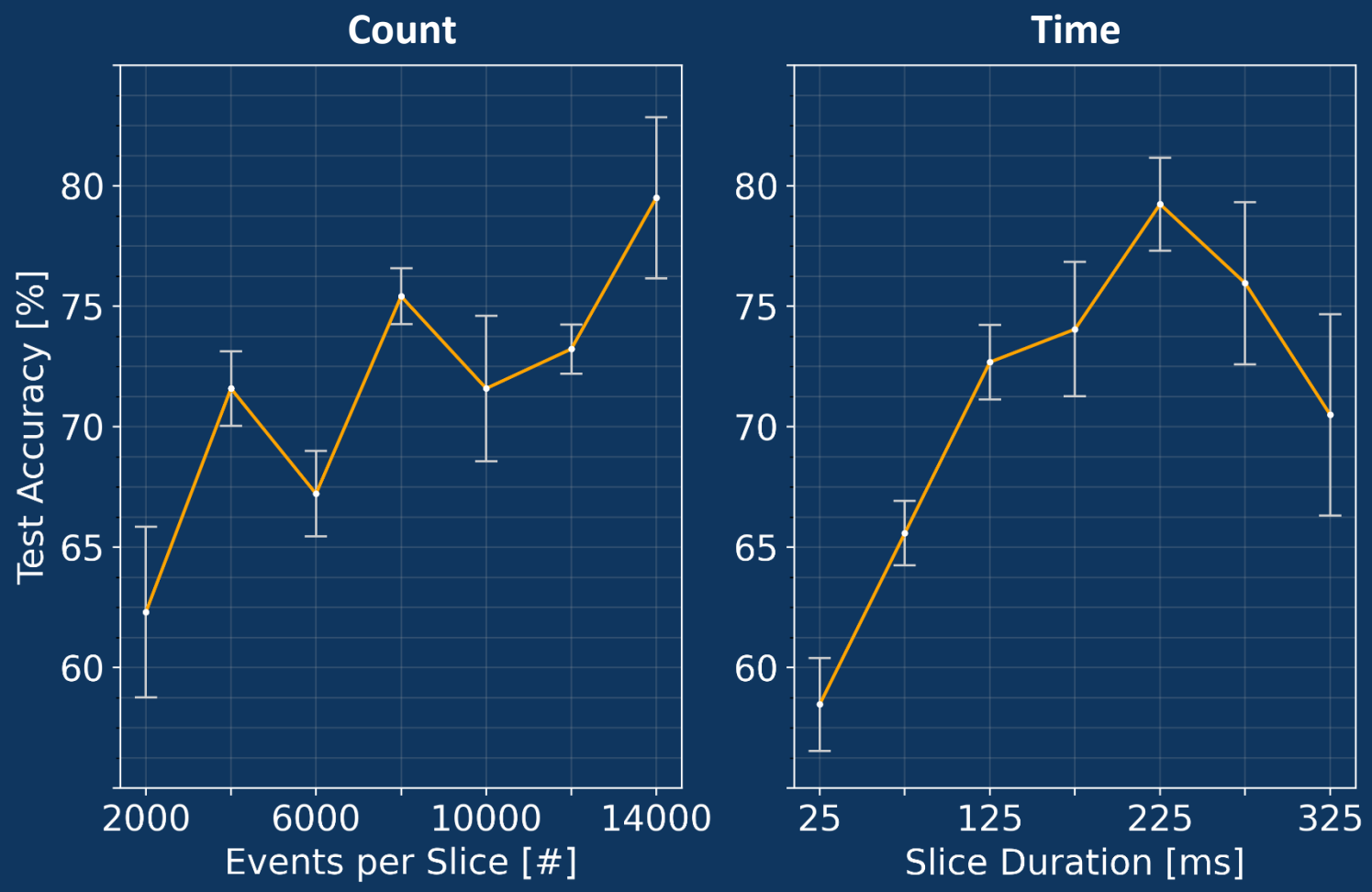
Accuracy

Model	Accuracy [%]		
	ASL DVS	DVS 128 Gesture	SL Animals DVS
SLAYER		93.64	60.9
STBP			56.2
GCNN	90.1		
EventNet	83.33		
PointNet++		97.08	
Timestamp CNN		97.35	
DGCNN		98.56	
Matrix LSTM	99.73		
EV-VGCNN	98.3		
HAREM Net	**98.1**	**88.5**	**73.2**

> State of the Art

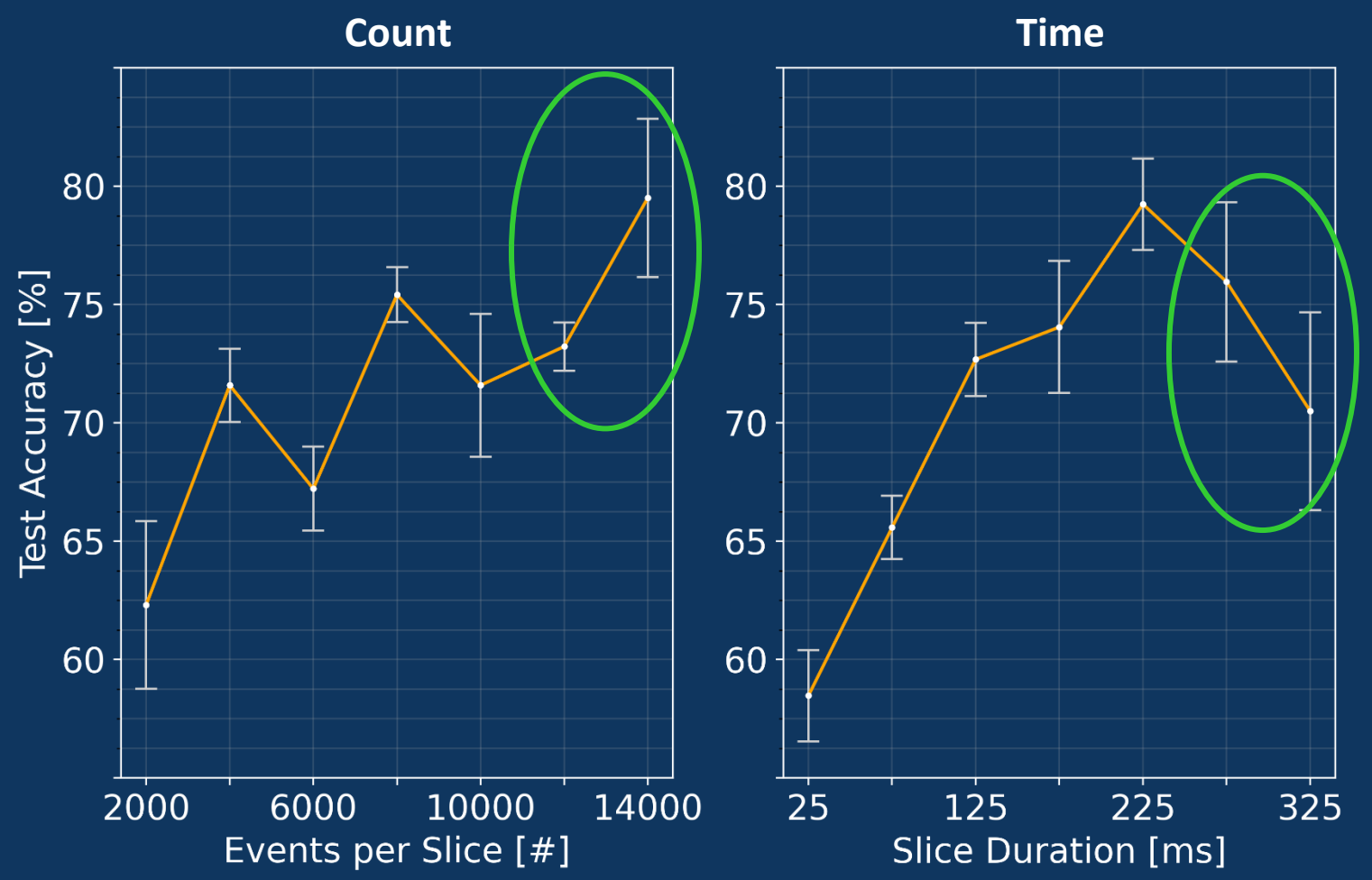
- Robust against noise
- Good on long sequences

Slicing



1000 Events ≈ 24 ms

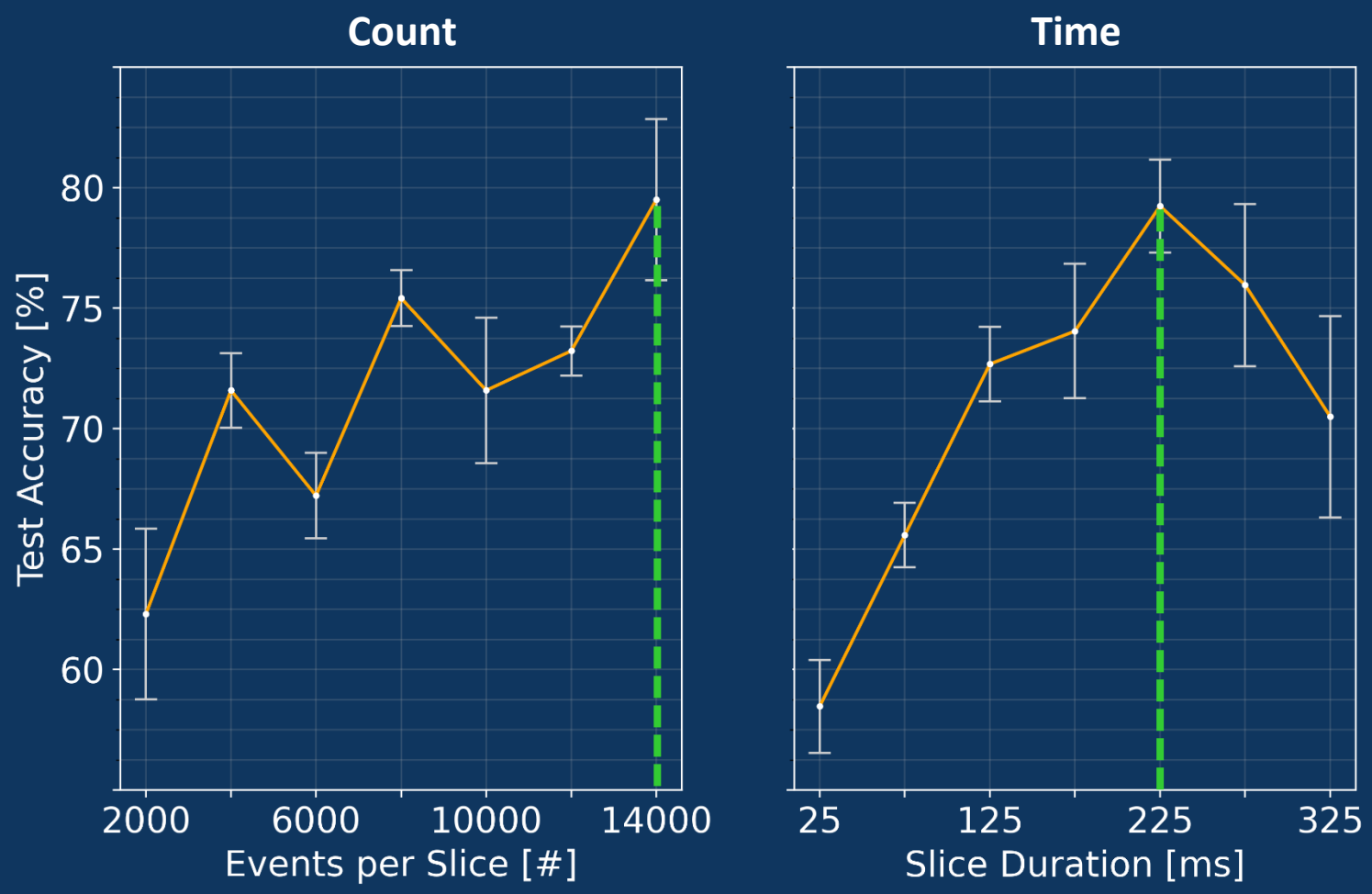
Slicing



1000 Events ≈ 24 ms

- Count > time for long slices

Slicing

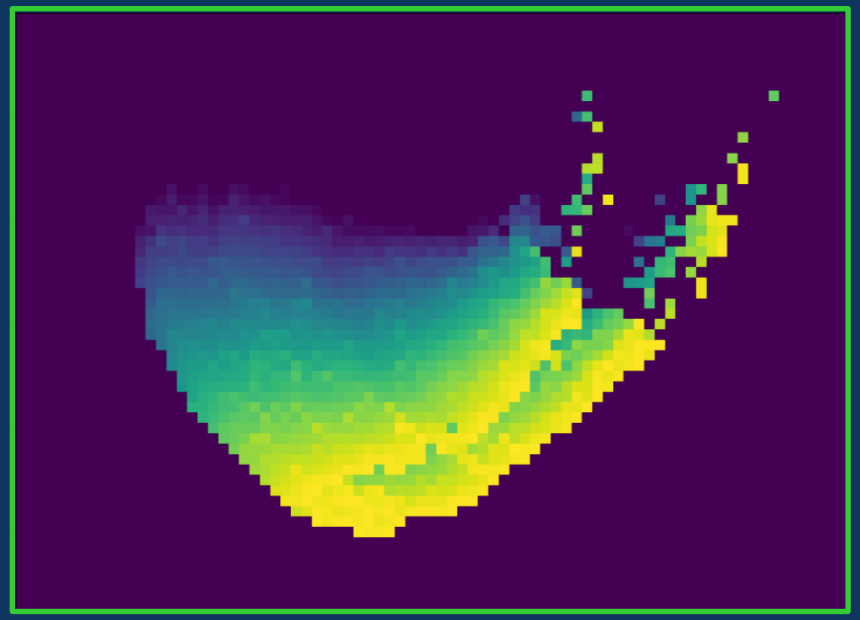


1000 Events ≈ 24 ms

- Count > time for long slices
- Time: Similar peak accuracy with shorter slices

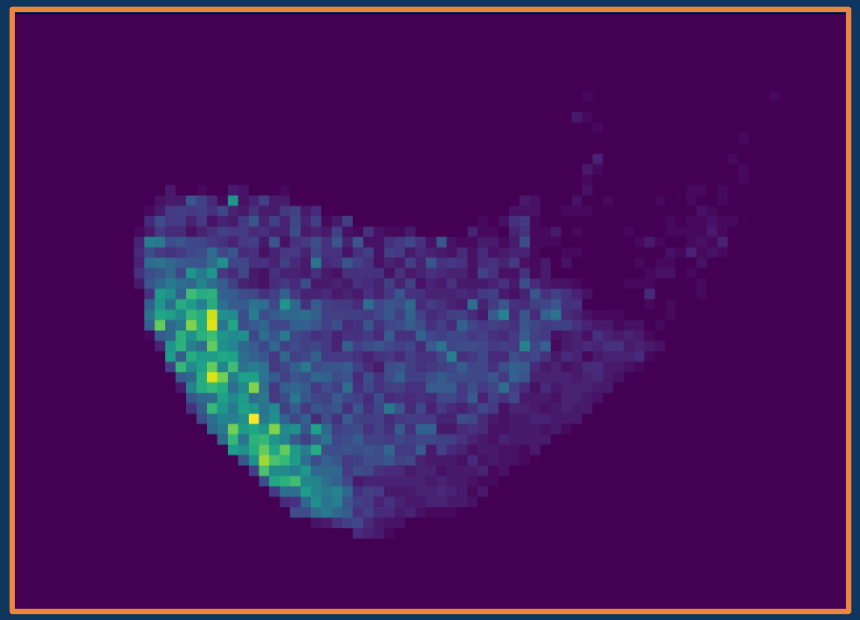
Voxel Feature

Timestamp Image



Per pixel: Time of last event

Event Image



Per pixel: Number of events in slice

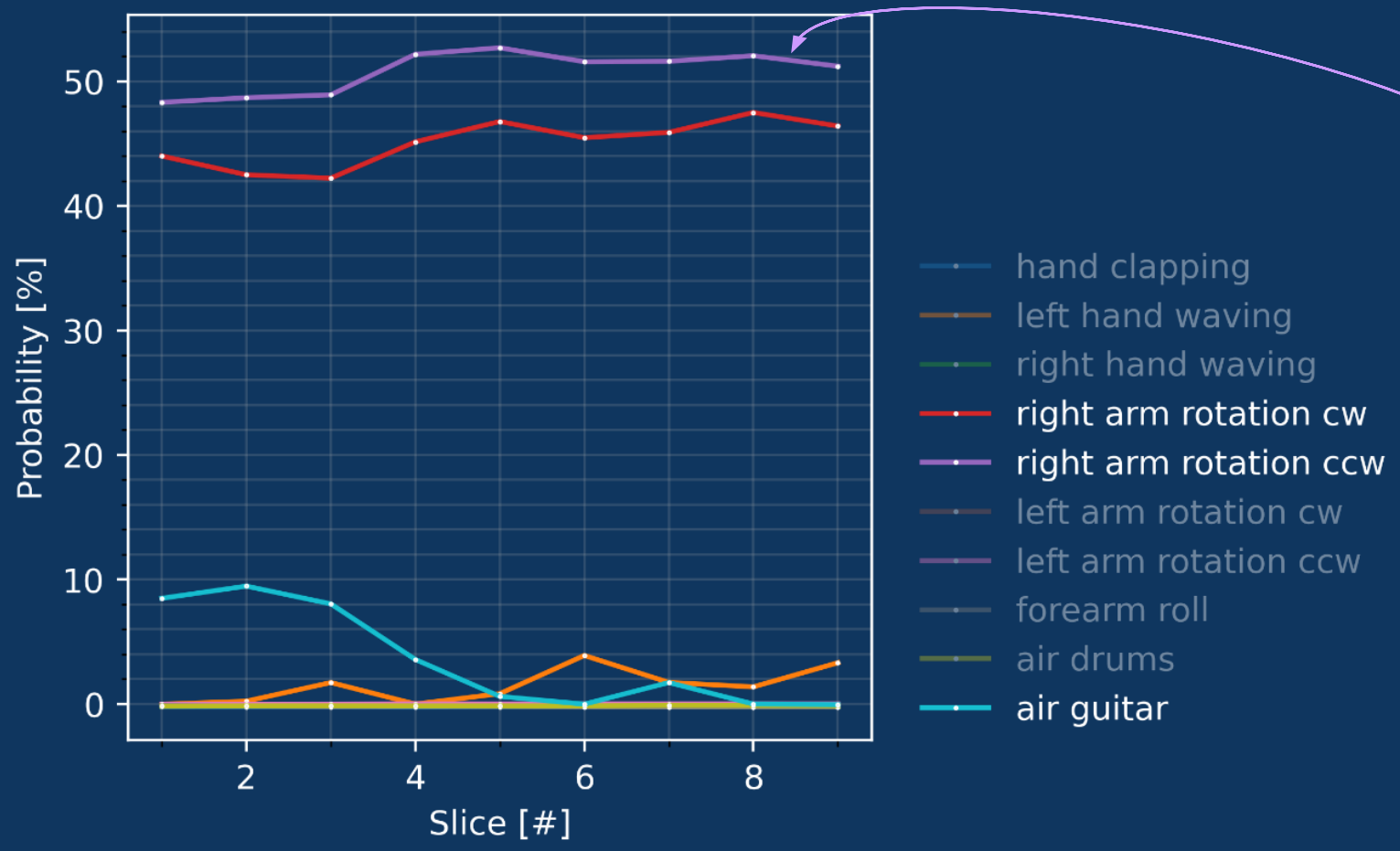
55 % Accuracy

Slice level:

Time information < Statistics

77 % Accuracy

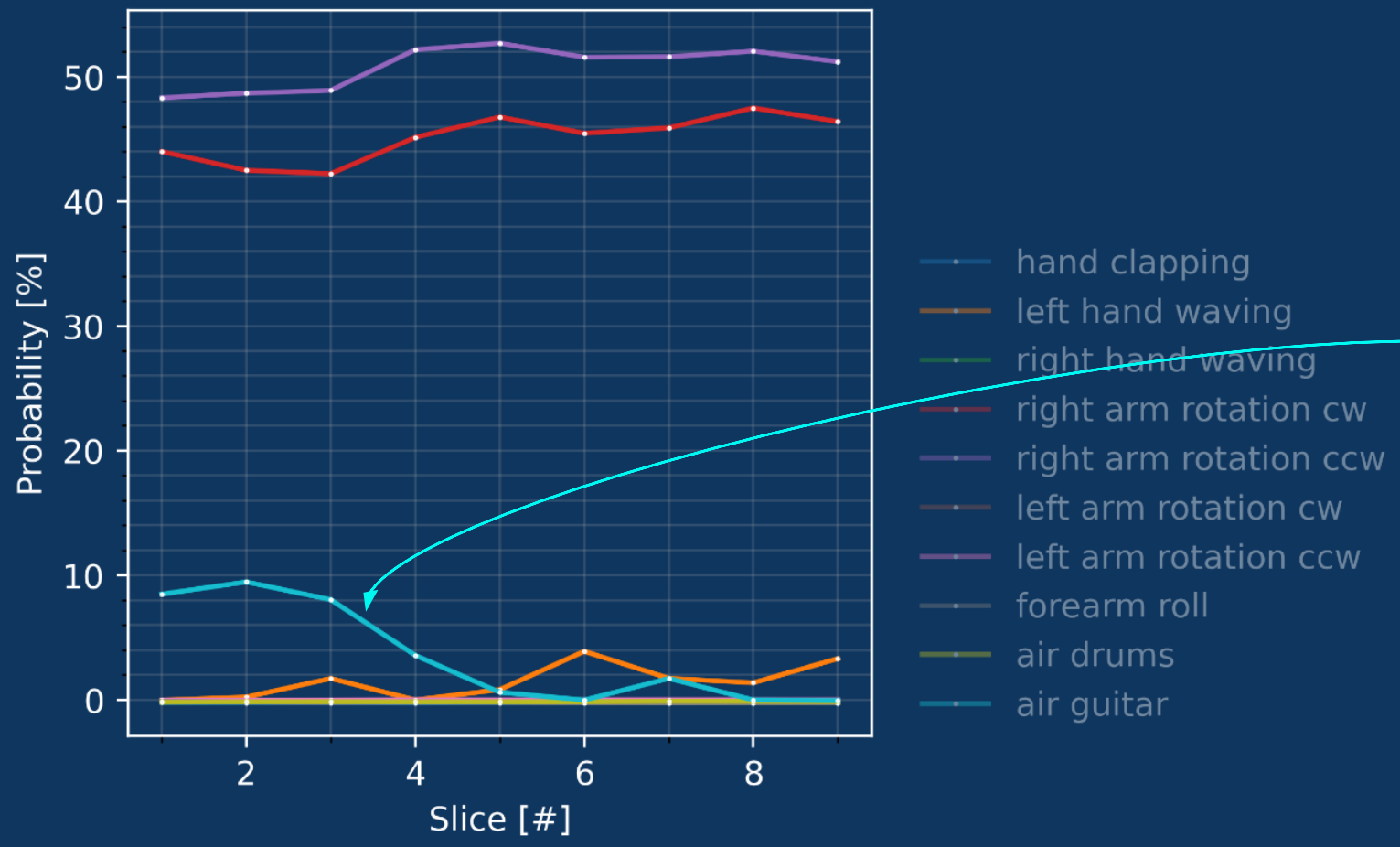
Confidence



- High-level information aggregation works:

- Correct class:
  Increases & scores high

Confidence

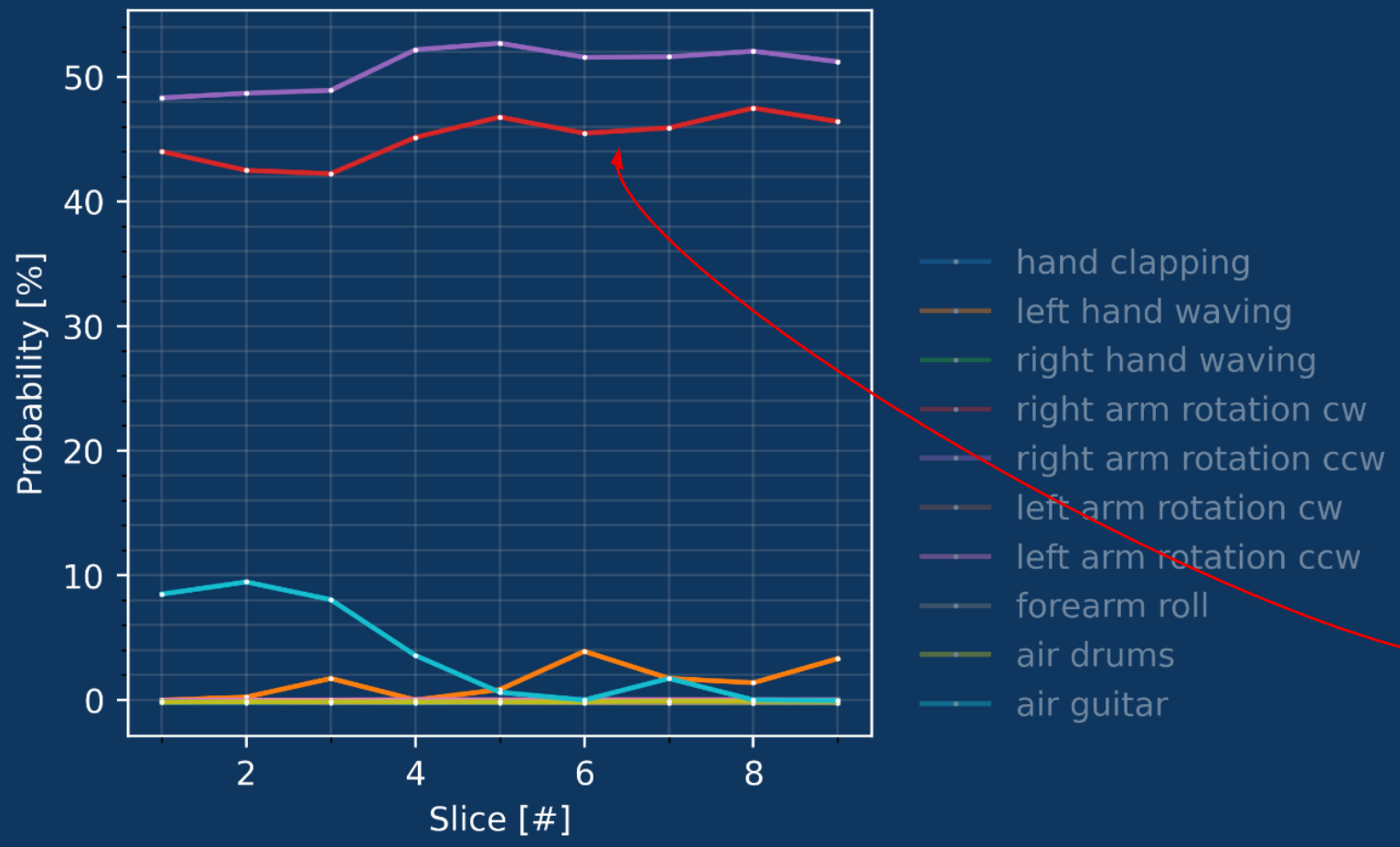


- High-level information aggregation works:

  - Correct class:
    Increases & scores high

  - Incorrect classes:
    Decrease & score low

Confidence



- High-level information aggregation works:

  - Correct class:
    Increases & scores high

  - Incorrect classes:
    Decrease & score low

  - Similar class:
    Closer probability

Problem

State of the Art

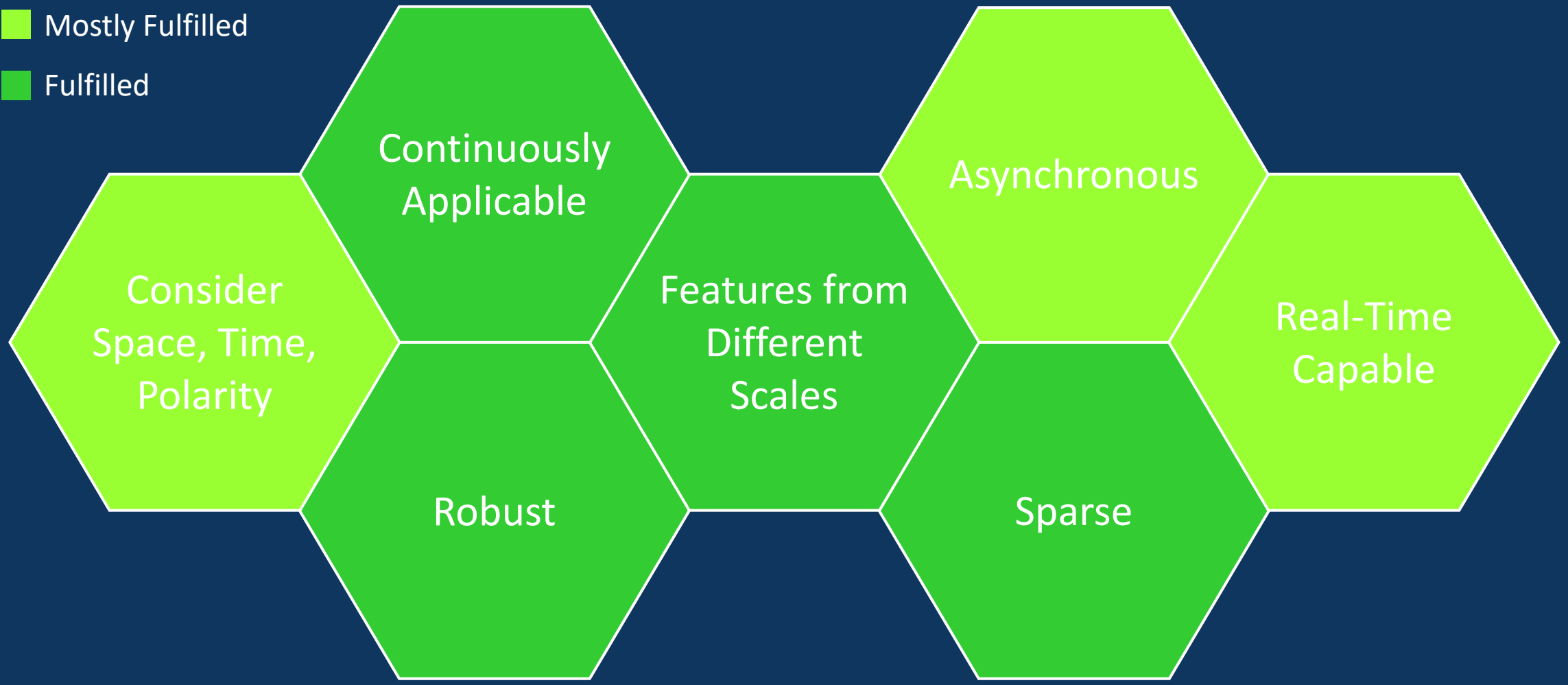
Concept

Results

Insights

Requirement Check

- Mostly Fulfilled
- Fulfilled



Research Questions

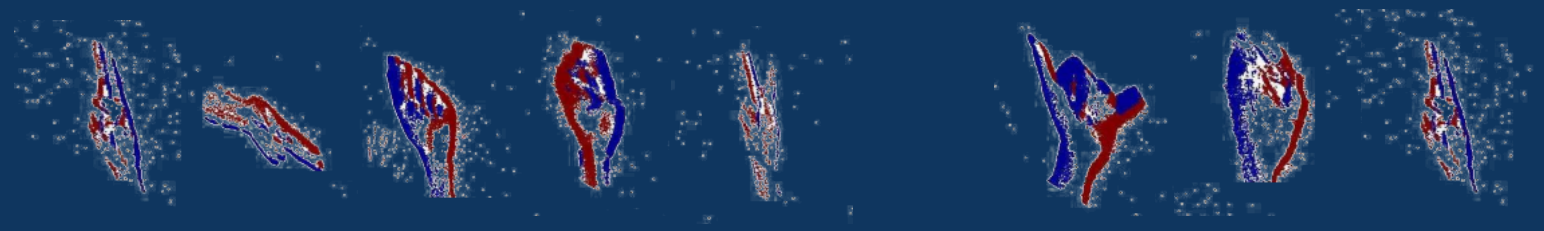
- How does **current AI** process event data?
- **Requirements** for processing that suits event data?
- **Develop model** according to requirements

Take Home

- AI approaches for event processing
  - CNN on 2D Representation
  - Sparse CNN
  - Sequence Processing
  - 3D Processing
- Processing model
  - Pre-Processing
  - Representation
  - Low-level features
  - High-level features
  - Backend
- Requirements ≠ conventional image processing e.g. sparse & asynchronous
- HAREM Net: Universal event processing network

Future Work

- Voxel Feature: Exploit polarity
- Aggregation: Include geometric information



HAREM
Net

Thank you

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