How Intermodal Interaction Affects the Performance of Deep Multimodal Fusion for Mixed-Type Time Series

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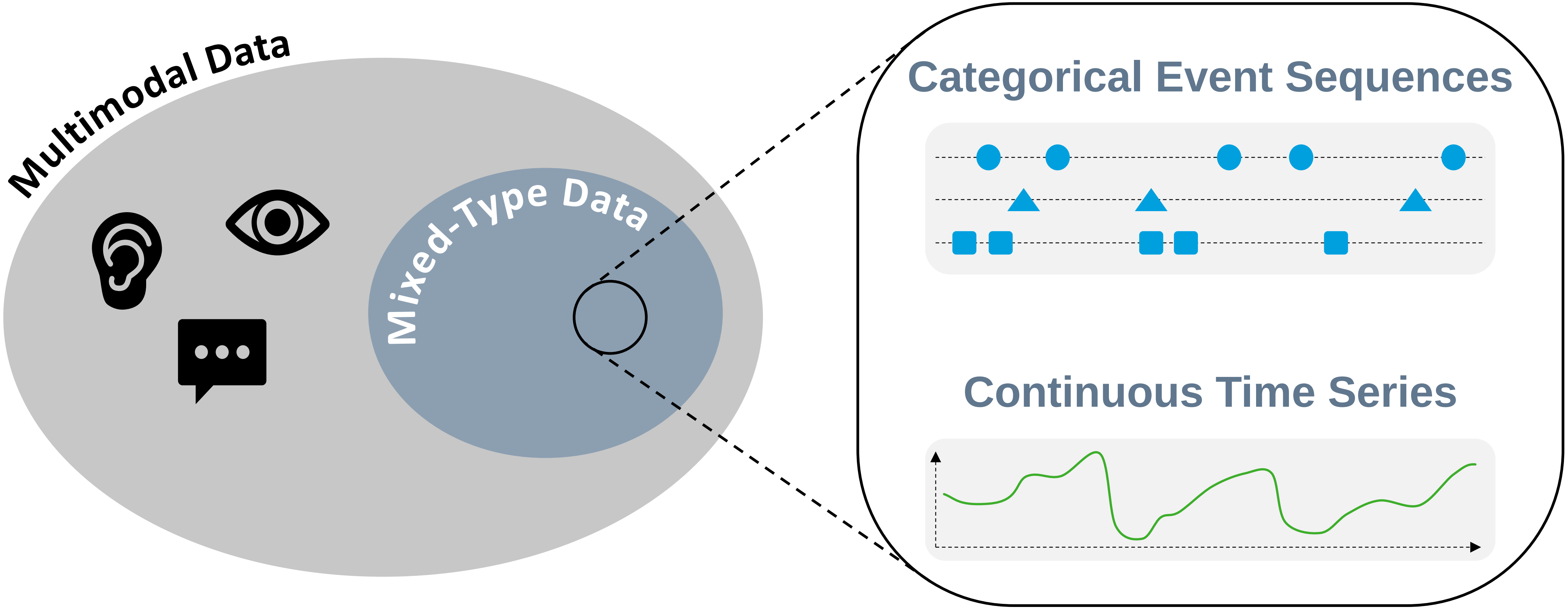
Multimodal Data

What is mixed-type time series?



Multimodal Data

Where can we find it?

Healthcare

- Medical Examinations
- Clinical Measurements

Human-Computer Interaction

- Button clicks
- Accelerometers

Industry

- Event logs
- Sensor measurements

Multimodal Data

Why is it important?

The presence of one modality can influence the perception of another

E.g. **MCGurck-Effect**

Letter | Published: 23 December 1976

Hearing lips and seeing voices

HARRY MCGURK & JOHN MACDONALD

Nature **264**, 746–748 (1976) | Cite this article

44k Accesses | **184** Altmetric | Metrics

2 Videos, same audio + **Different lip movements** → **Different perceived audio**

Fusion Types and Methods

Fusion Type

When are modalities fused

- **Late Fusion**
- **Intermediate Fusion**
- **Early Fusion**

Fusion Method

How are modalities fused

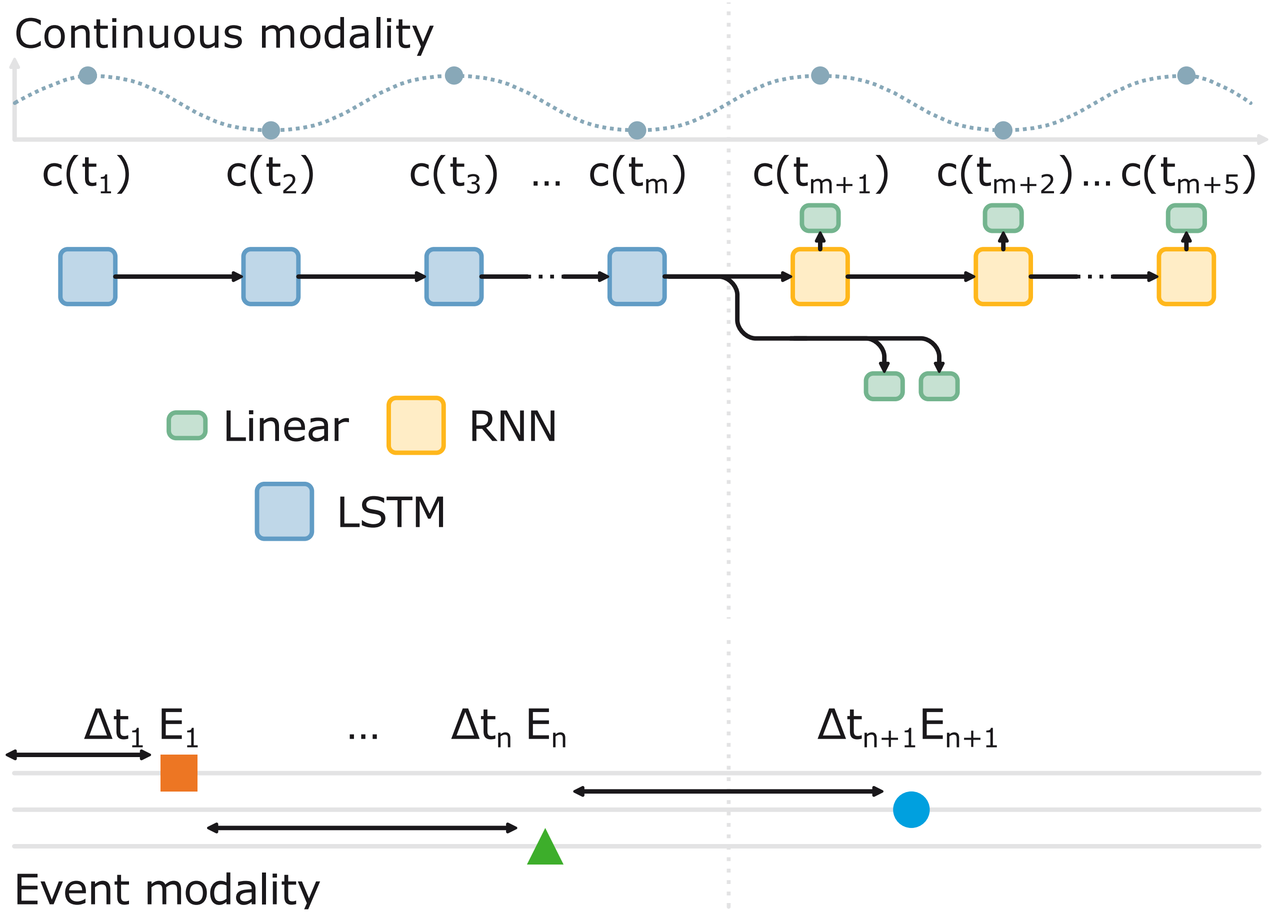
- **Concatenation**
- **Weighted Mean**
- **Gating**
- **…**

Main Topics

How does the nature of the data
influece the optimal fusion approach

Fusion Types

Unimodal (no fusion)



Unimodal Baselines

- No Fusion
- Forecast based on a single modality

Fusion Types

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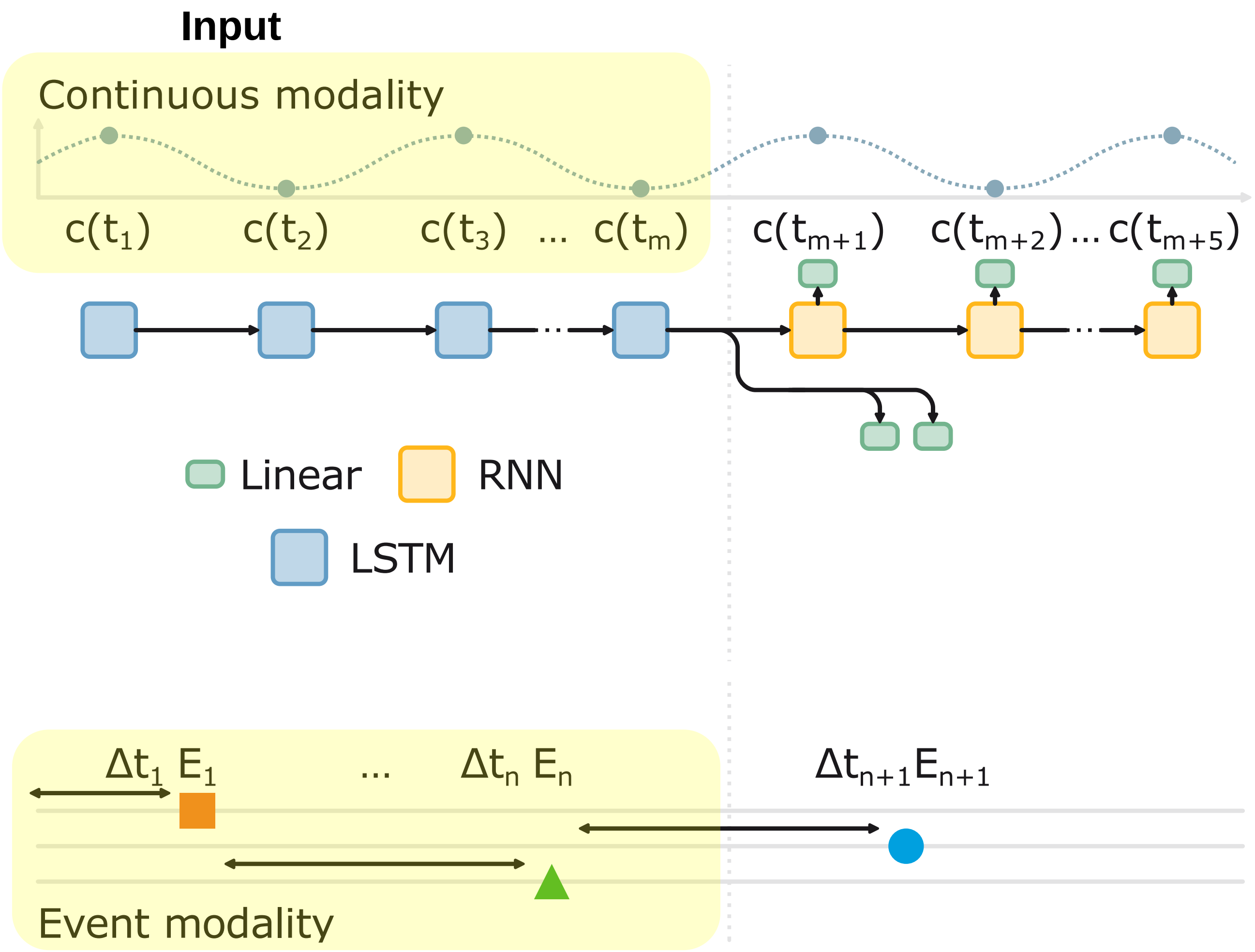

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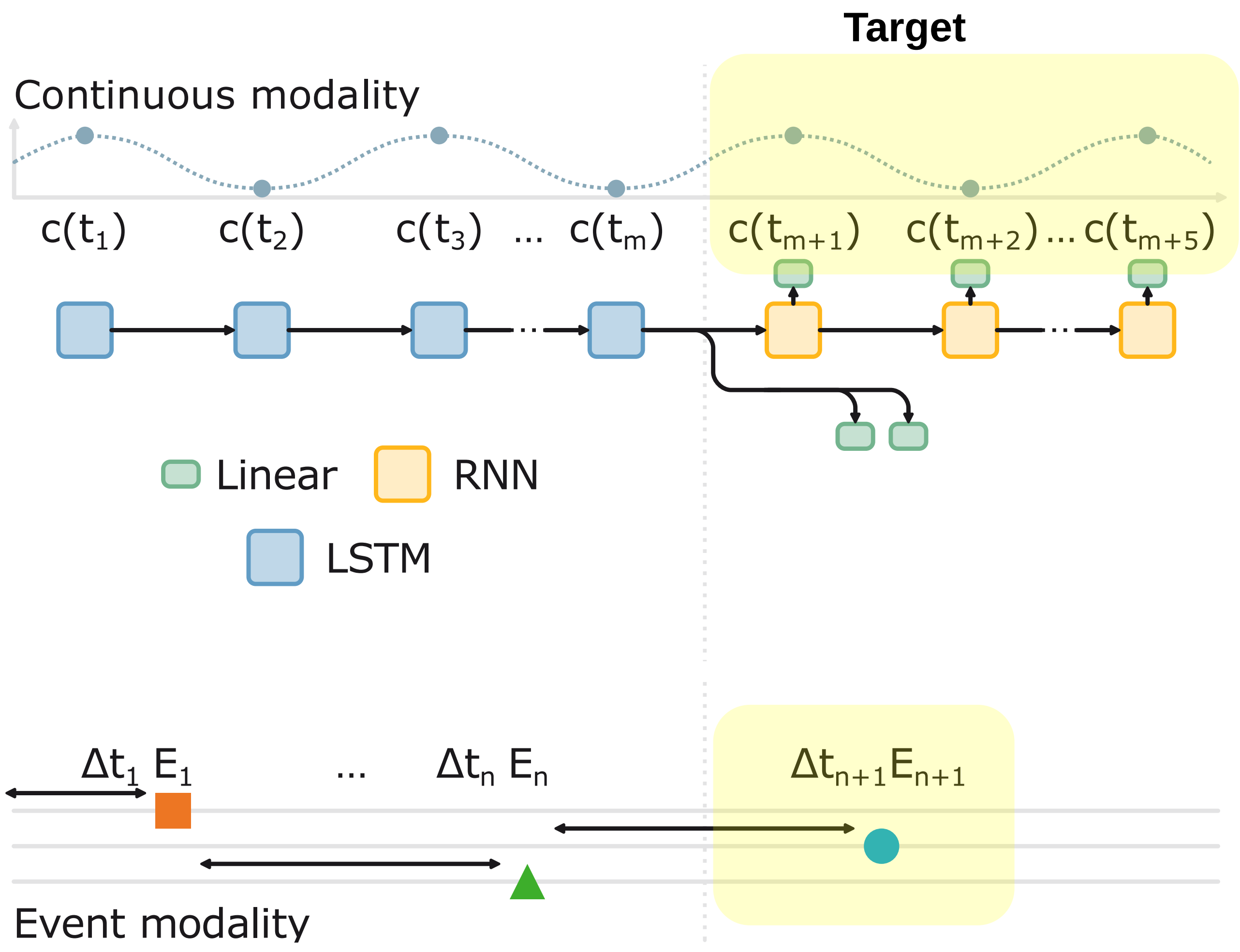

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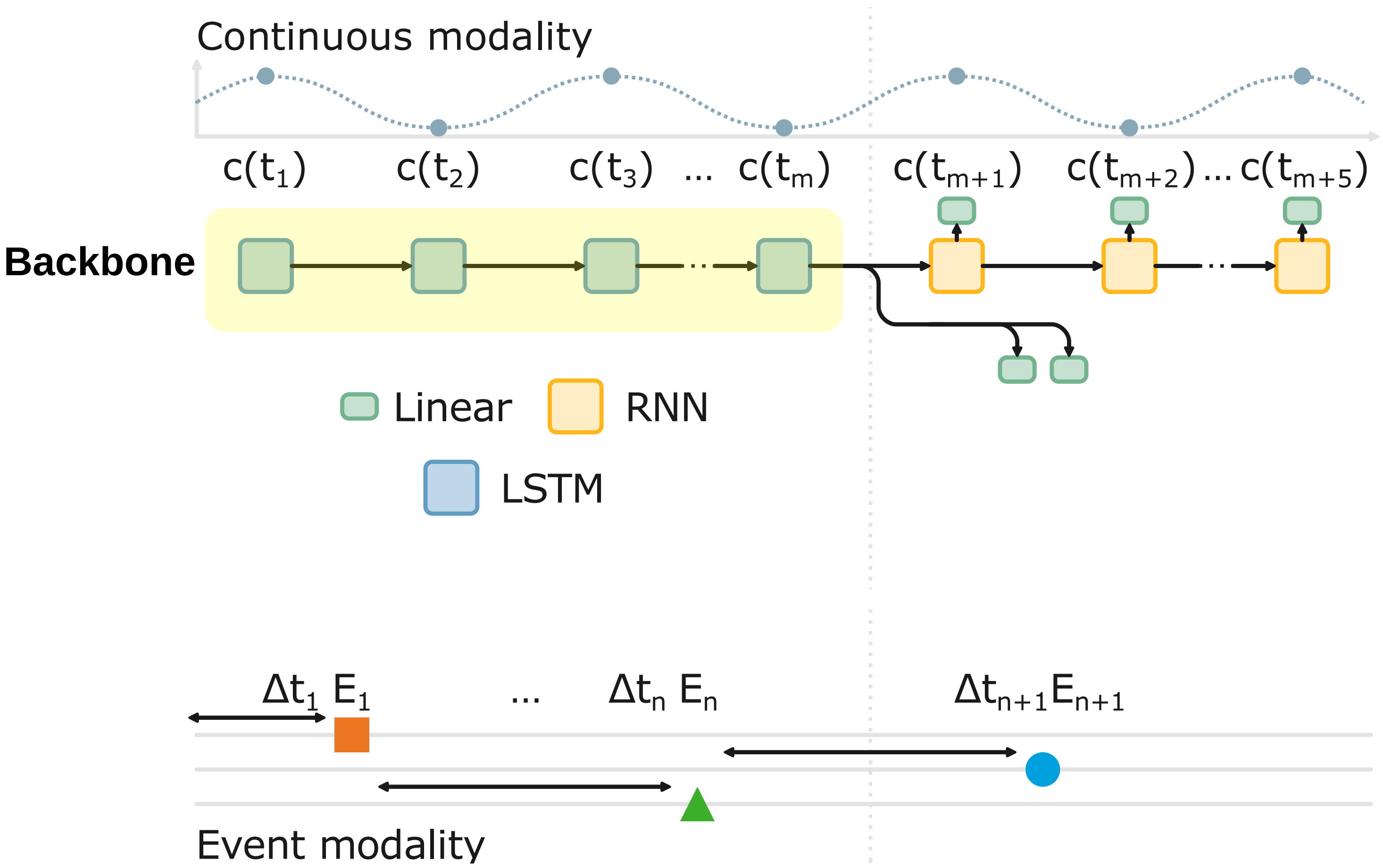

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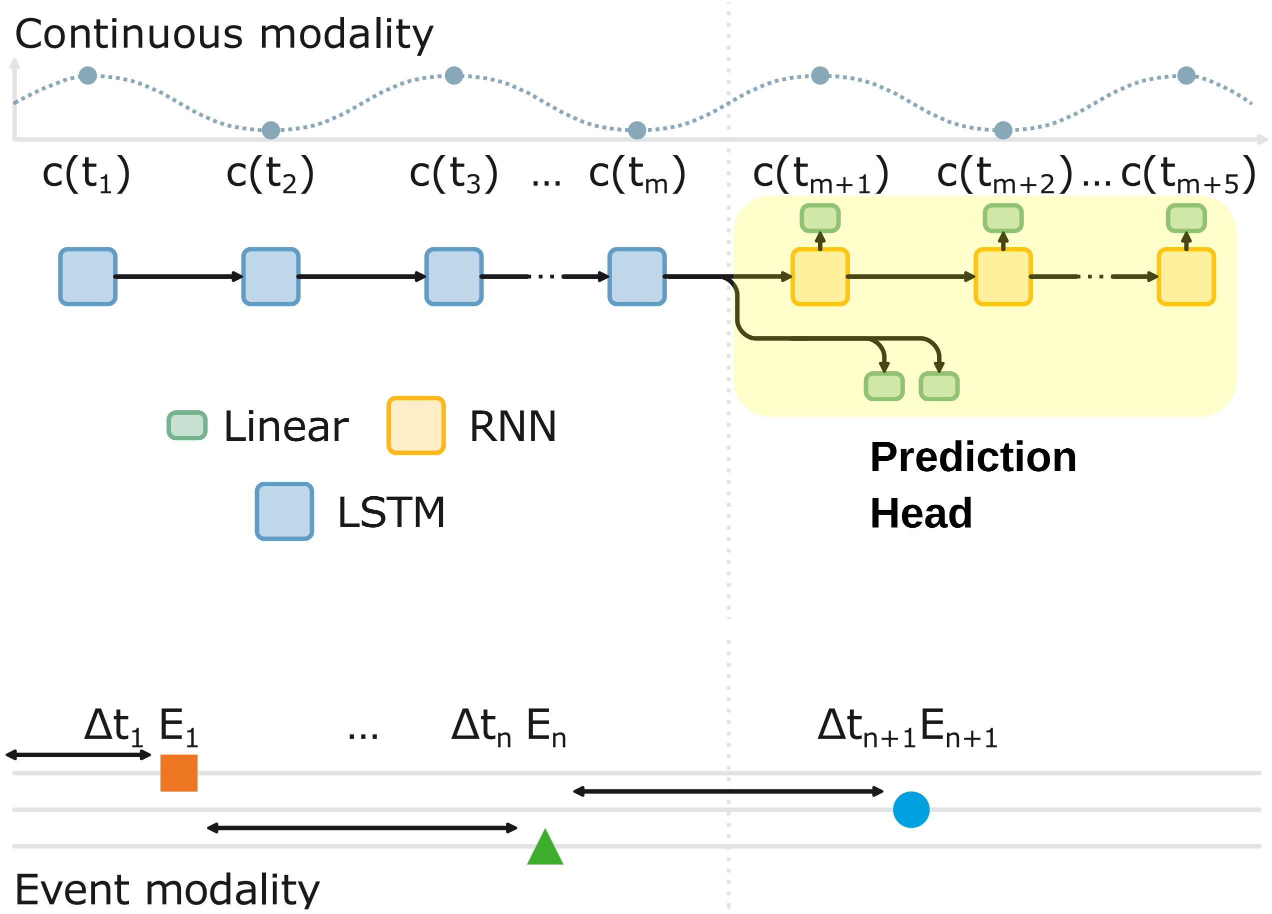

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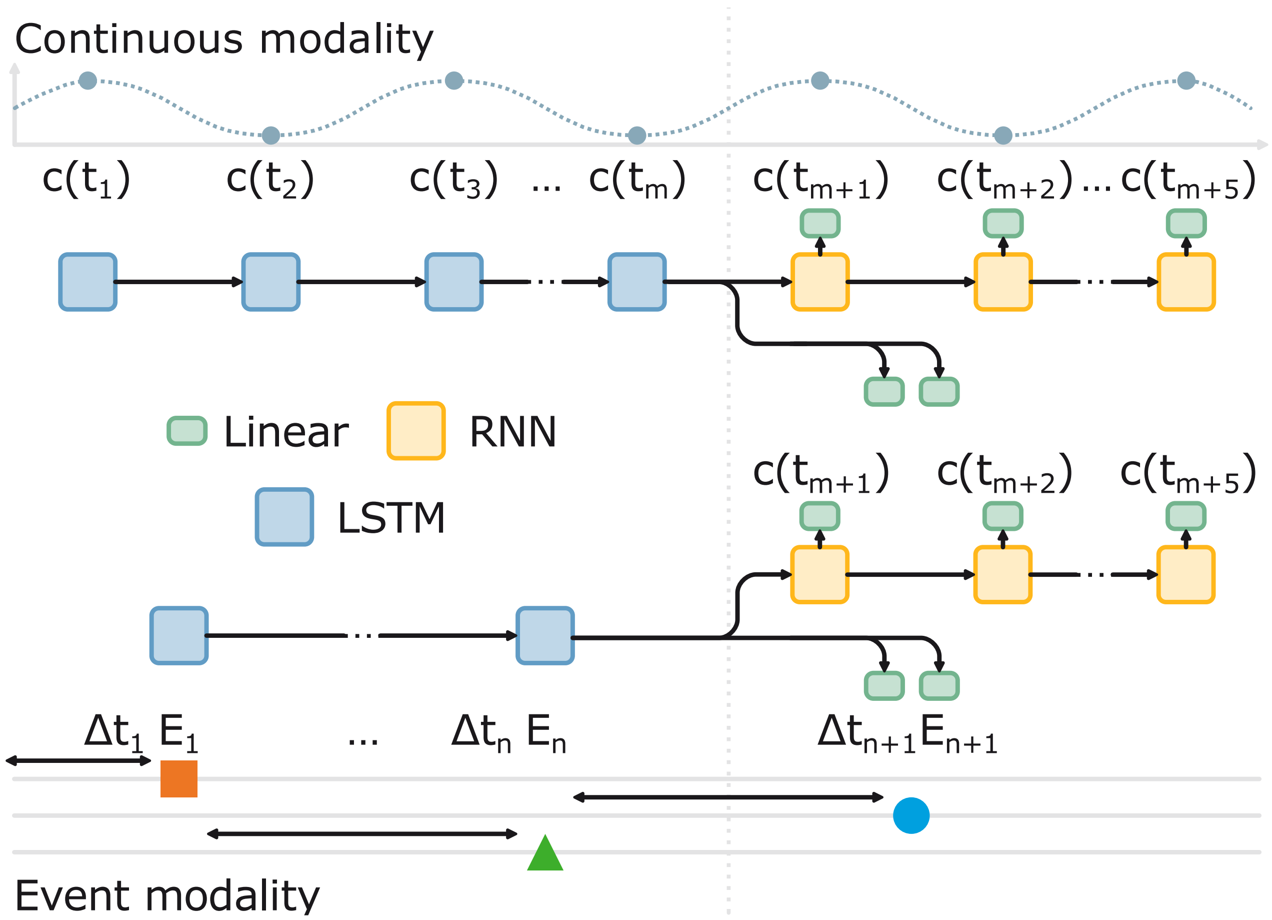

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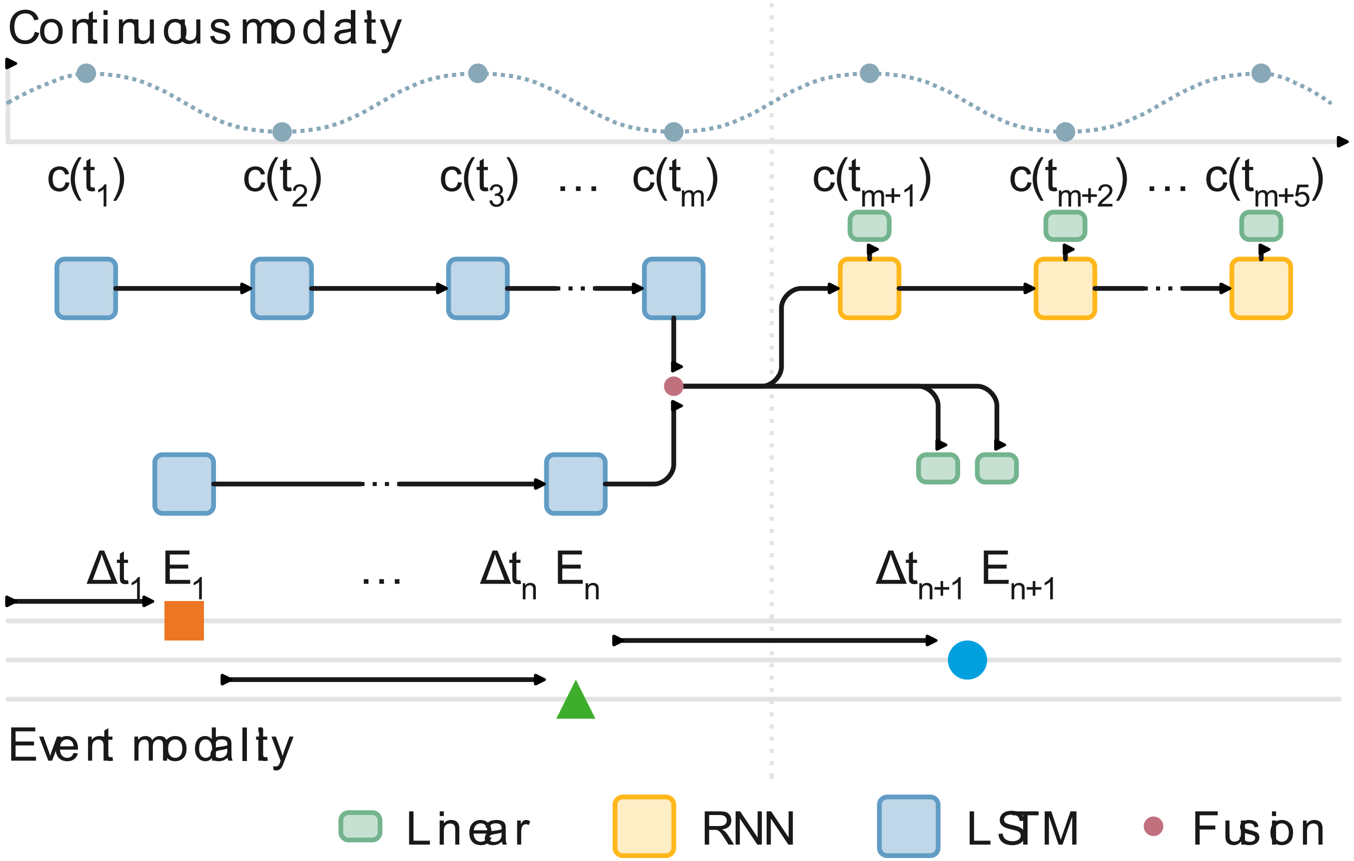
Fusion Types

Intermediate Fusion

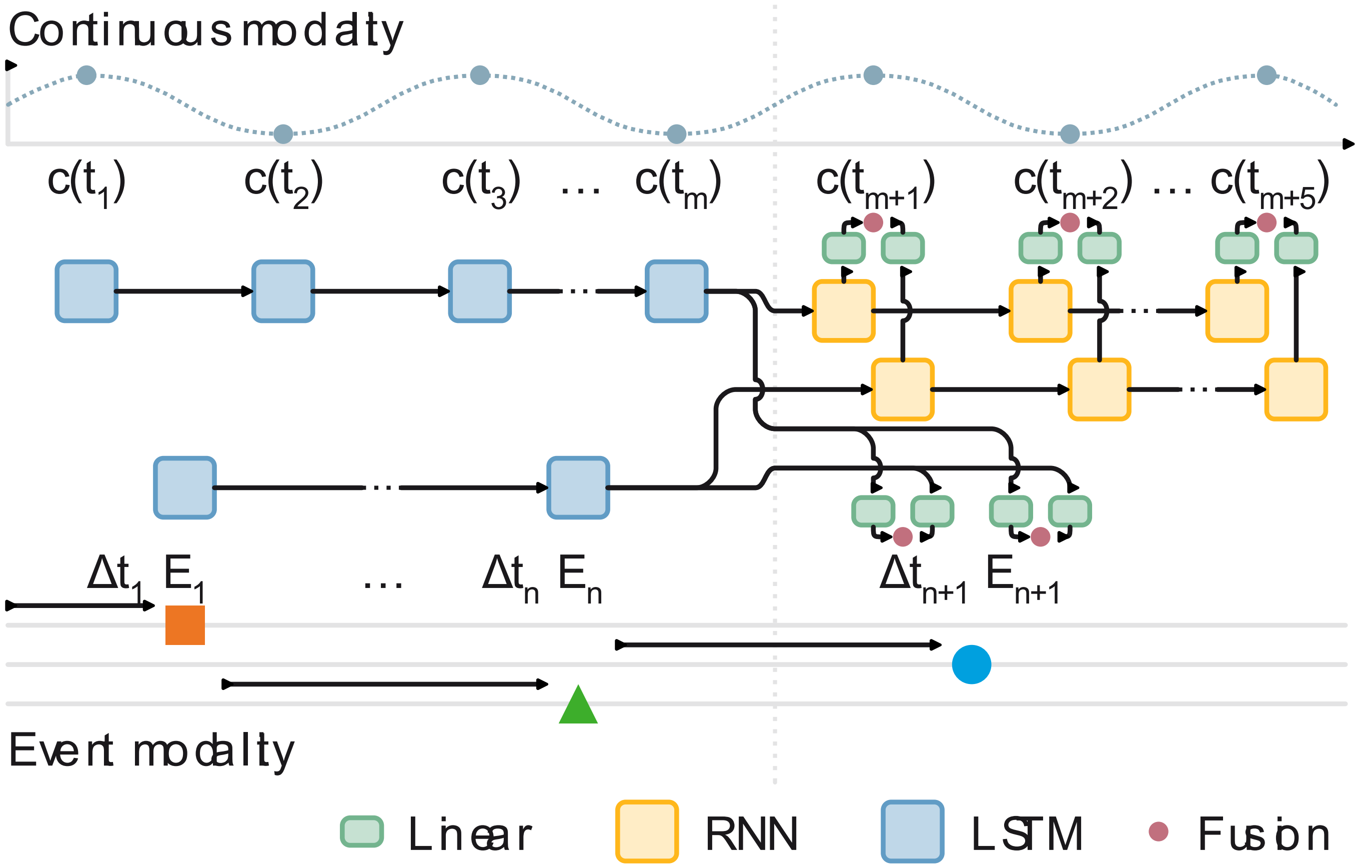


Intermediate Fusion

- 2 Backbones + 1 Prediction Head
- Fuse final unimodal representations
- One forecast based on both modalities

Fusion Types

Late Fusion

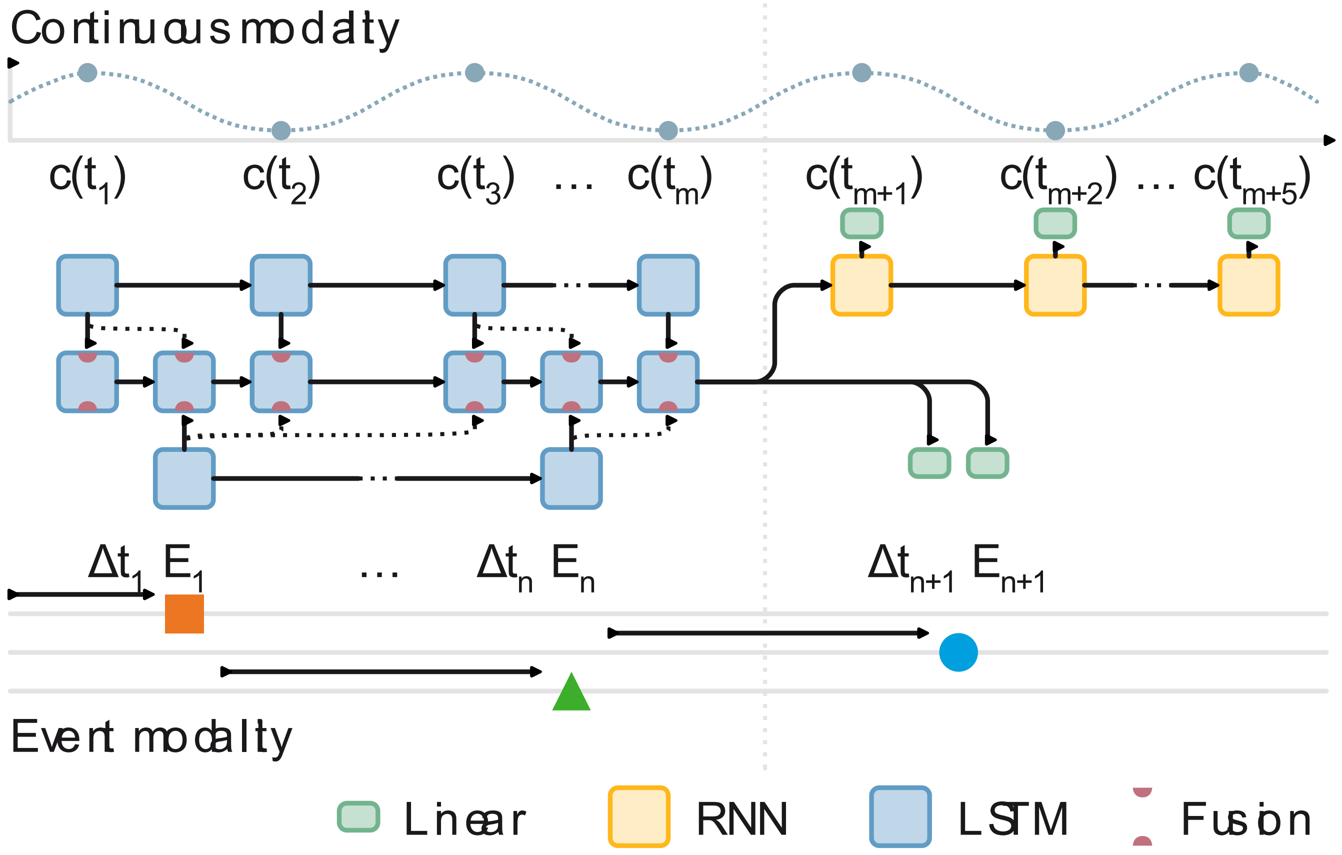


Late Fusion

- 2 Backbones + 2 Prediction Heads
- One model per modality
- Unimodal predictions are fused

Fusion Types

Early Fusion



Early Fusion

- 1 common Backbone + 1 Prediction Head
- 2 unimodal + 1 multimodal LSTM
- Unimodal representations are fused at each timestep

Fusion Methods

- Concatenation
- Weighted mean
- Weighted mean with correlation [Yang 2017]
- Gating [Arevalo 2017, Narayanan 2020]
- Feature sharing [Wang 2015]

Deep Multimodal Representation Learning from Temporal Data

Xitong Yang*[1], Palghat Ramesh[2], Radha Chitta*[3], Sriganesh Madhvanath*[3], Edgar A. Bernal*[4] and Jiebo Luo[5]

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GATED MULTIMODAL UNITS FOR INFORMATION FUSION

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MMSS: Multi-modal Sharable and Specific Feature Learning for RGB-D Object Recognition

Anran Wang[1], Jianfei Cai[1], Jiwen Lu[2], and Tat-Jen Cham[1]
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Gated Recurrent Fusion to Learn Driving Behavior from Temporal Multimodal Data

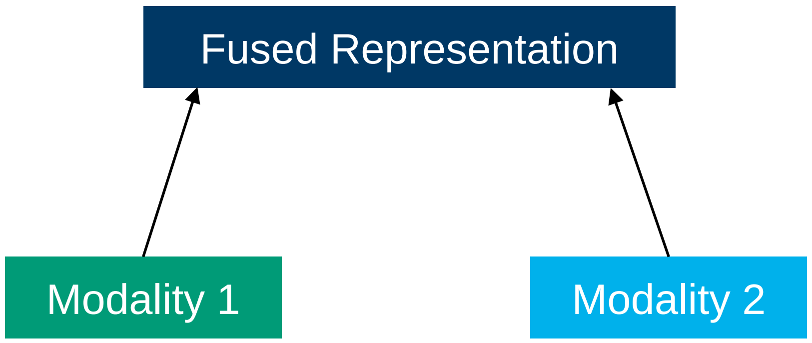
Athma Narayanan, Avinash Siravuru, and Behzad Dariush

Fusion Methods

1. Concatenation

- Simple approach that propagates the maximum amount of information.

- Can result in large representations with redundant features.

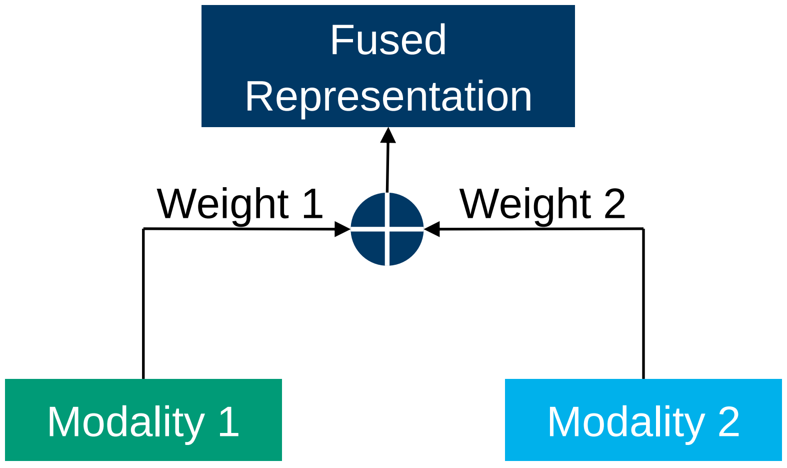


Fusion Methods

1. Concatenation

2. **Weighted Mean**

- Representations need to be of equal size.
- Smaller feature size compared to concatenation.
- Weighting can account for modality importance.



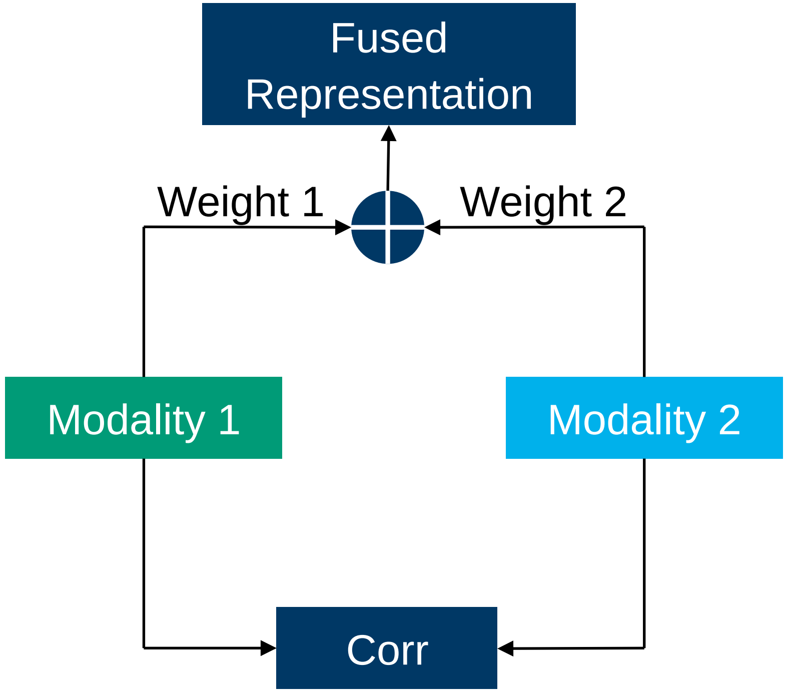
Fusion Methods

1. Concatenation
2. Weighted Mean
3. **Weighted Mean with coordinated representations**

- Calculate correlation and subtract from prediction loss.

$$L = L_{prediction} - \tau \, Corr$$

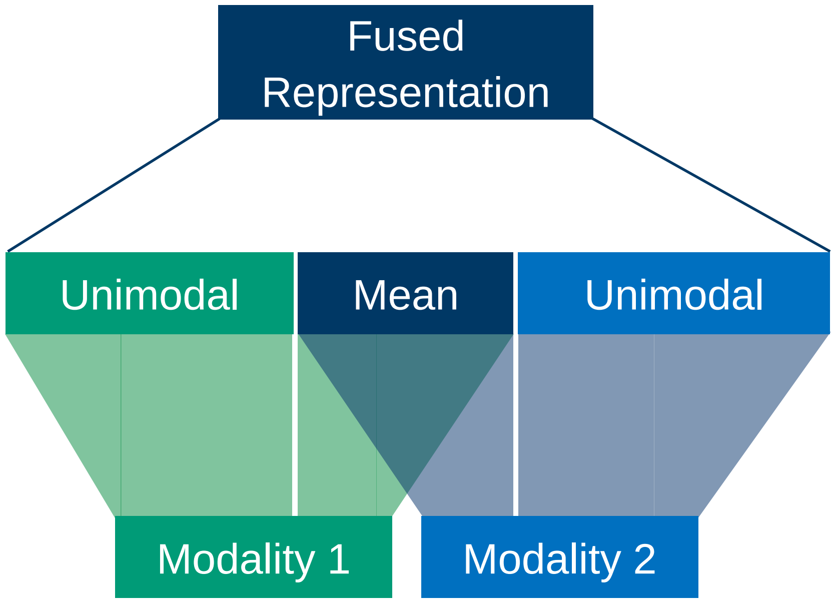
- Coordinating representations can improve the performance [Yan17].



Fusion Methods

1. Concatenation
2. Weighted Mean
3. Weighted Mean with coordinated representations.
4. **Shared Features**

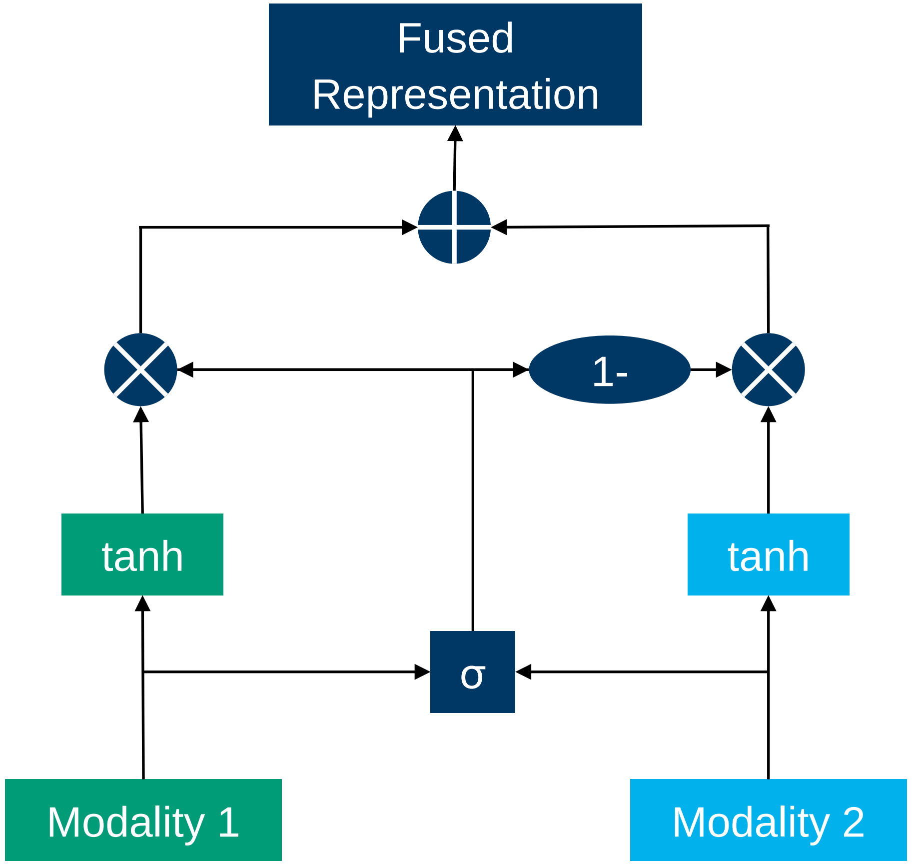
- Middle ground between concatenation and averaging.
- Based on Wan et. al. [Wan15].



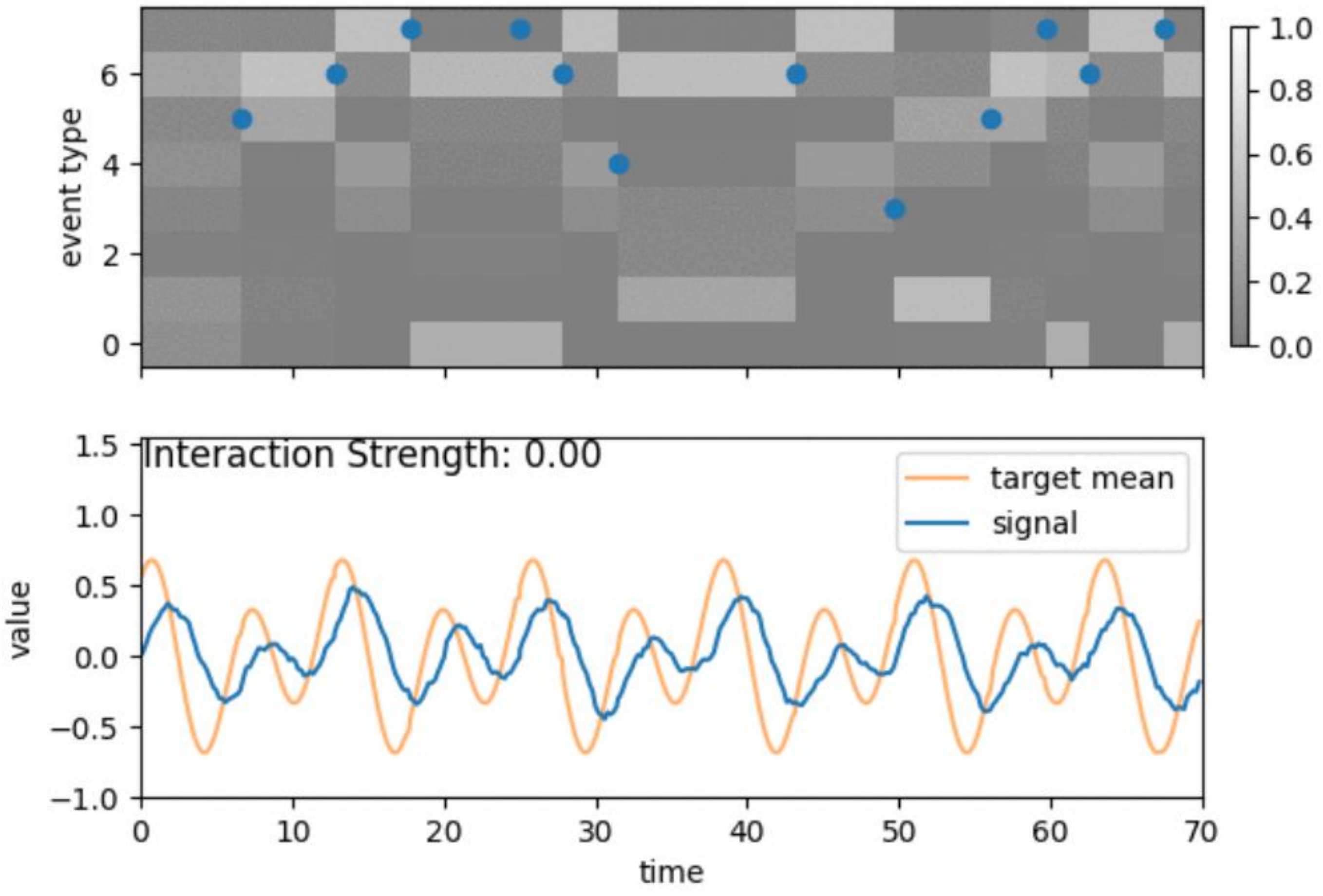
Fusion Methods

1. Concatenation
2. Weighted Mean
3. Weighted Mean with coordinated representations.
4. Shared Features
5. **Gating**

- Flexible weighting of each feature.
- Can help with model explainability.
- Proposed by Arevalo et. al. [Are17].



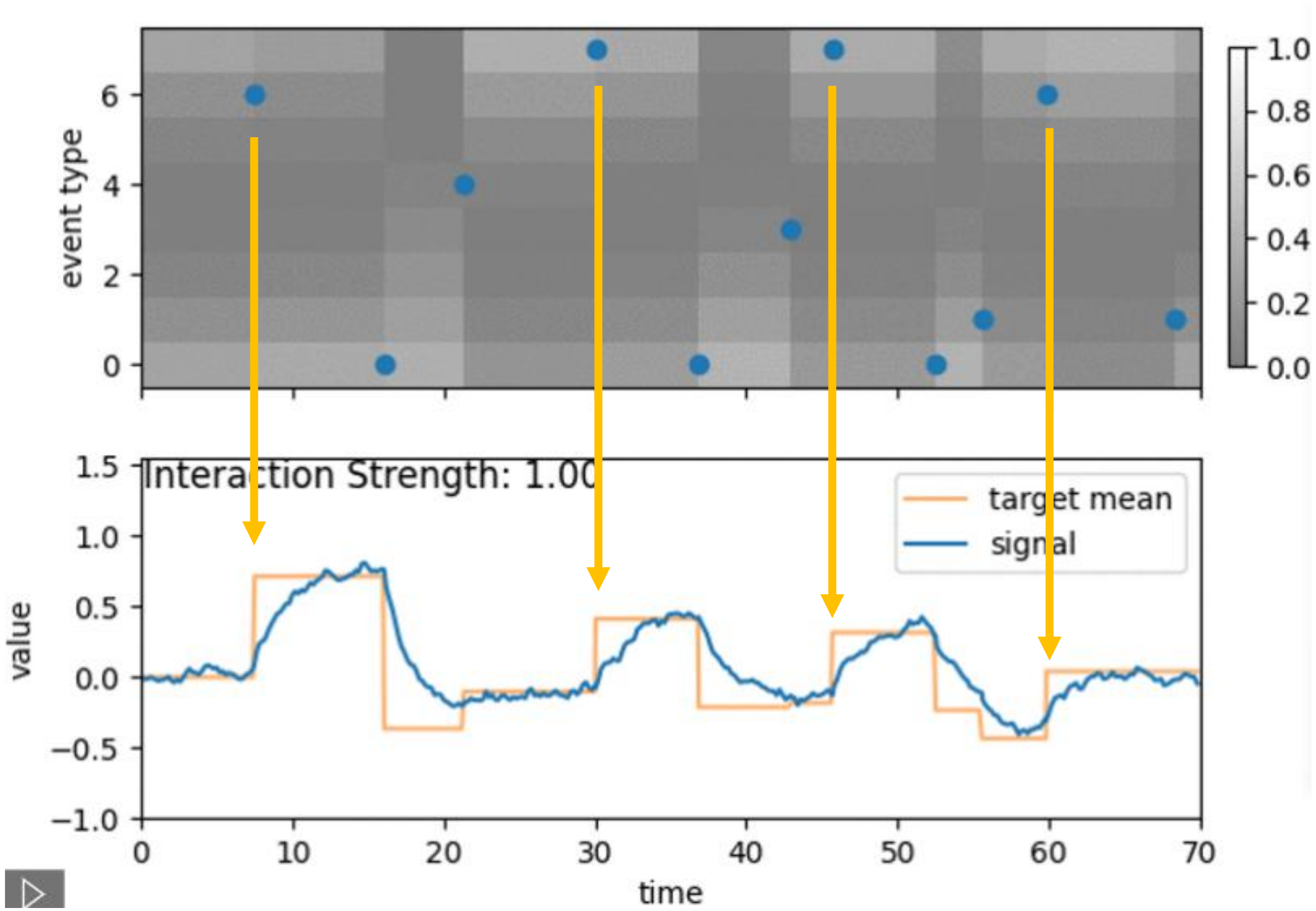
Synthetic Data



No Interaction

- Fixed transition prop.
  most likely transitions:
  - 5->6, 6->7, 7->6
- Sinusoidal base Signal

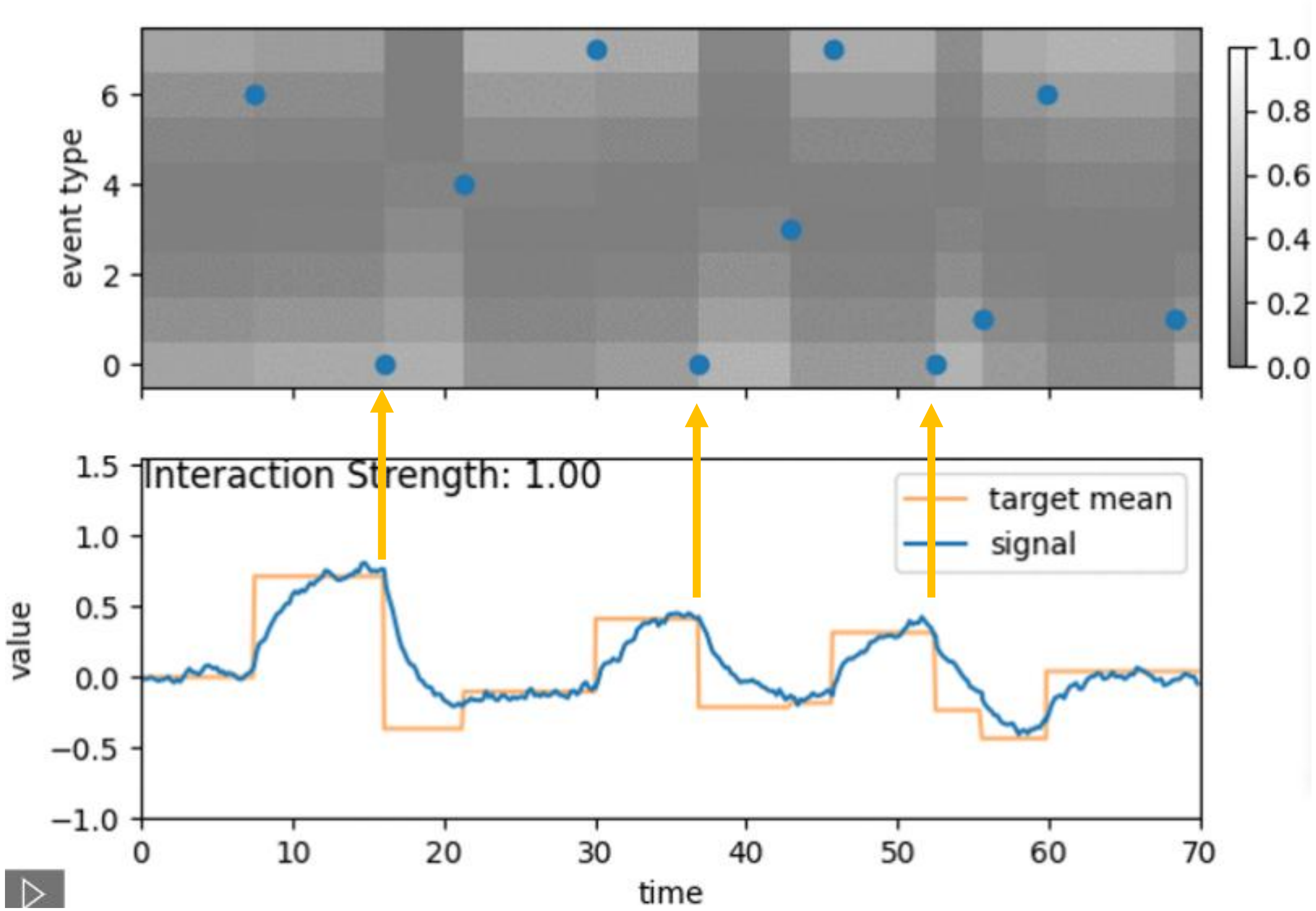
Synthetic Data



Full Interaction

- Event 7&6 → increase in target mean

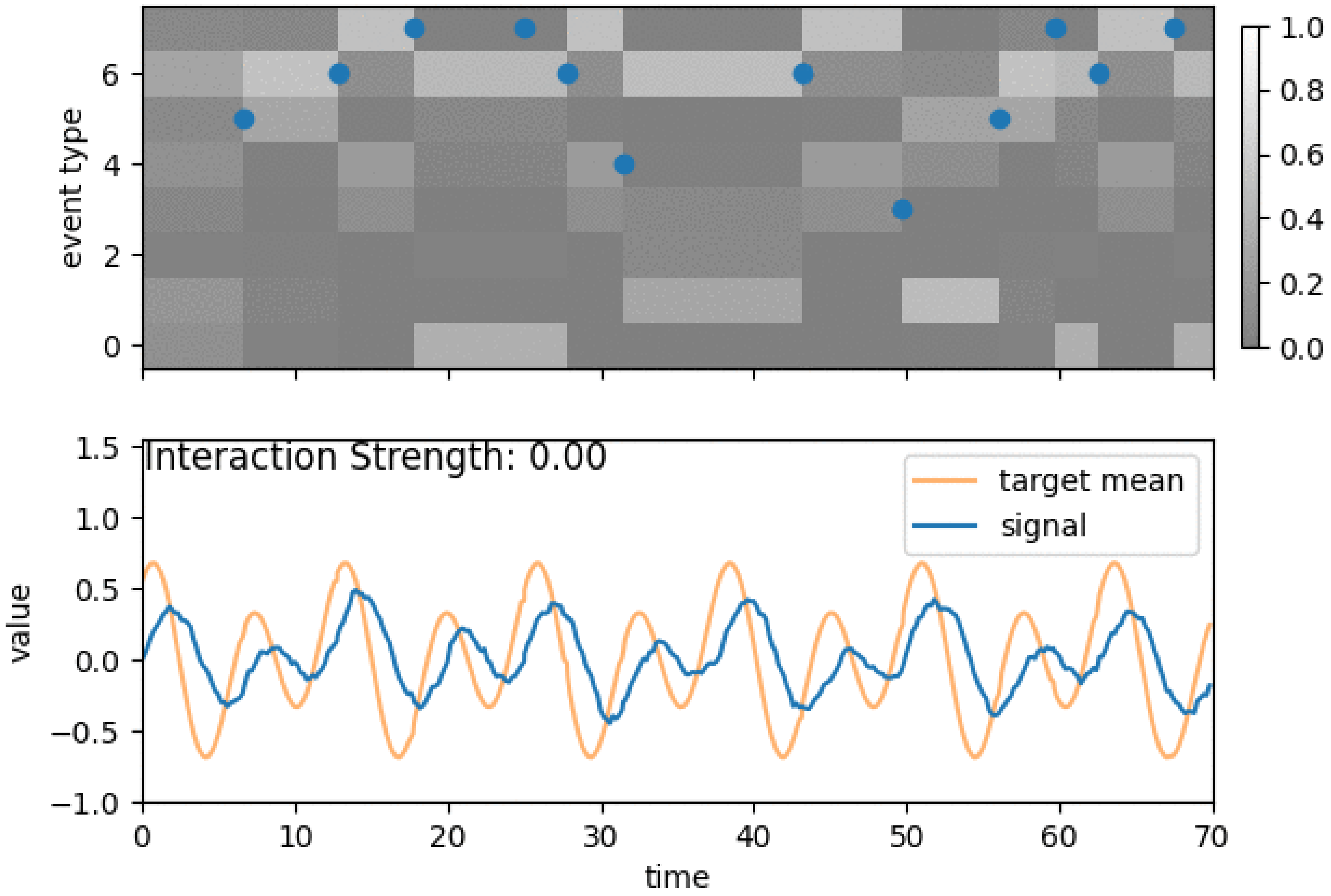
Synthetic Data



Full Interaction

- Event 7&6 → increase in target mean
- High cont. Signal → Event 0 is likely

Synthetic Data



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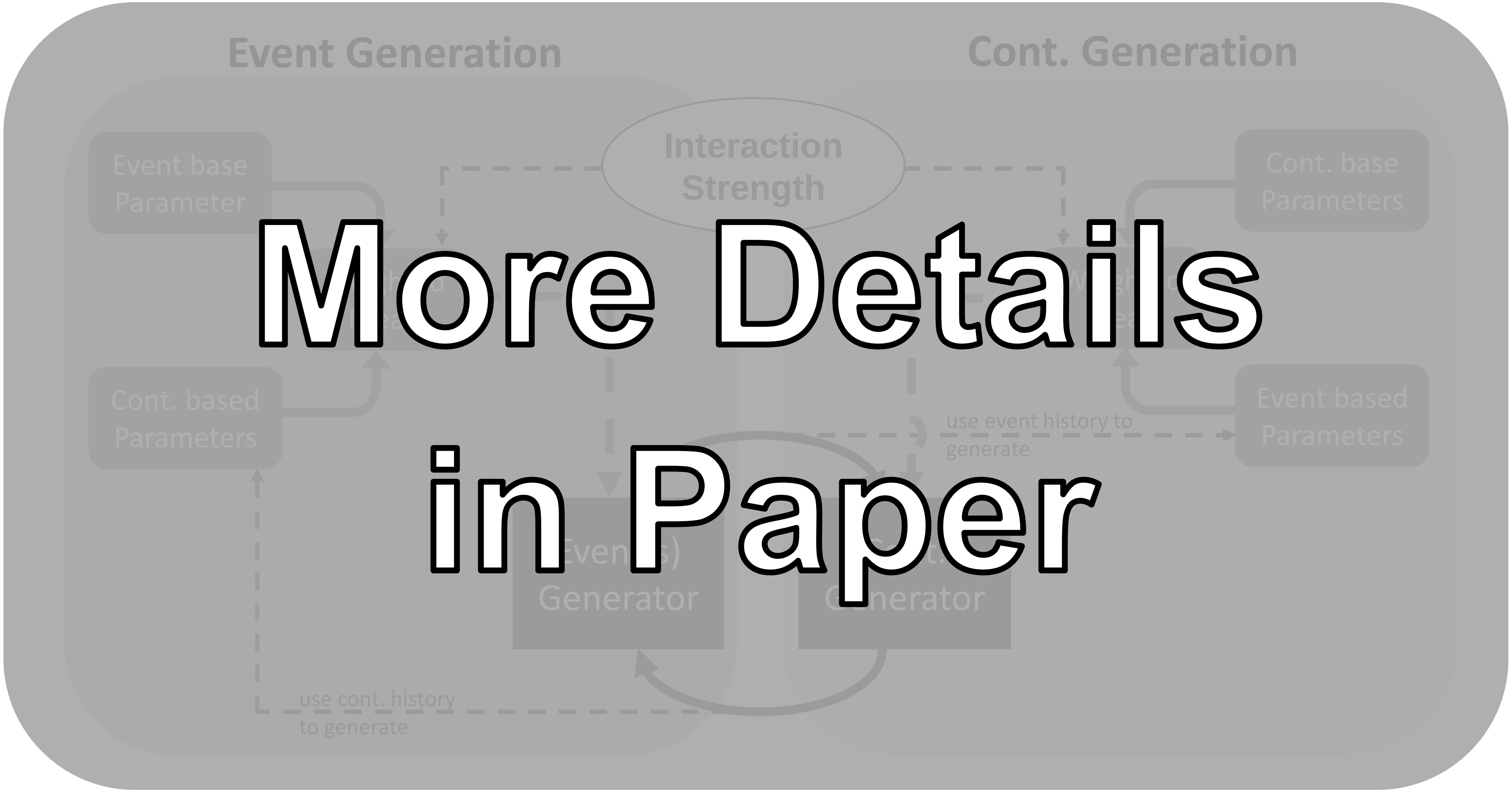

More Details in Paper

Mixed-Type Time Series Forecasting

Results

type	method	synthetic MTTS			electrical grid			MazeBall		
		cont.	Δt	event	cont.	Δt	event	cont.	Δt	event
early	cat.	*0.044*	**0.067**	**0.899**	1.623	*0.056*	0.728	<u>2.867</u>	**0.105**	**0.717**
	mean	**0.040**	<u>0.082</u>	*0.887*	1.603	0.057	0.735	3.912	<u>0.109</u>	0.702
	corr.	0.046	0.093	0.887	1.886	0.059	0.710	3.348	0.115	0.696
	gating	<u>0.041</u>	*0.084*	<u>0.887</u>	*1.574*	<u>0.056</u>	*0.738*	3.463	*0.109*	0.703
	share	0.050	0.099	0.878	1.592	0.057	0.737	3.106	0.111	0.705
inter.	cat.	0.049	0.098	0.876	<u>1.573</u>	0.057	<u>0.740</u>	3.747	0.115	0.704
	mean	0.055	0.111	0.855	1.591	0.057	0.731	3.193	0.115	0.692
	corr.	0.045	0.085	0.880	1.738	0.059	0.638	4.296	0.112	0.704
	gating	0.049	0.087	0.872	1.723	0.056	0.710	*2.909*	0.110	0.702
	share	0.050	0.099	0.873	**1.552**	**0.055**	**0.742**	2.924	0.113	0.704
late	mean	0.059	0.171	0.759	1.751	0.062	0.719	**2.626**	0.113	0.705
	corr.	0.058	0.162	0.763	1.823	0.062	0.704	3.486	0.113	*0.706*
uni.	cont.	0.049	0.472	0.680	1.826	0.074	0.579	3.763	0.154	0.664
	event	0.146	0.445	0.622	2.692	0.059	0.737	5.060	0.109	<u>0.708</u>

Mixed-Type Time Series Forecasting

Results

Datasets

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Mixed-Type Time Series Forecasting

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Forecasting Metric   Datasets

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Mixed-Type Time Series Forecasting

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Mixed-Type Time Series Forecasting

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	corr.	0.058	0.162	0.763	1.823	0.062	0.704	3.486	0.113	*0.706*
uni.	cont.	0.049	0.472	0.680	1.826	0.074	0.579	3.763	0.154	0.664
	event	0.146	0.445	0.622	2.692	0.059	0.737	5.060	0.109	0.708

Conclusion

- The **strength** and **direction** of intermodal interactions affect the optimal fusion strategy

- **Early Fusion**
  - Good at capturing low-level bidirectional interactions
  - Best performance when the interaction strength is medium (both modalities carry relevant information)

- **Concatenation** often beats more sophisticated fusion methods

The best forecasting approach depends on the nature of the time series

Thank you for your attention

Marginalization