Relation Inference among Sensor Time Series in Smart Buildings with Metric Learning

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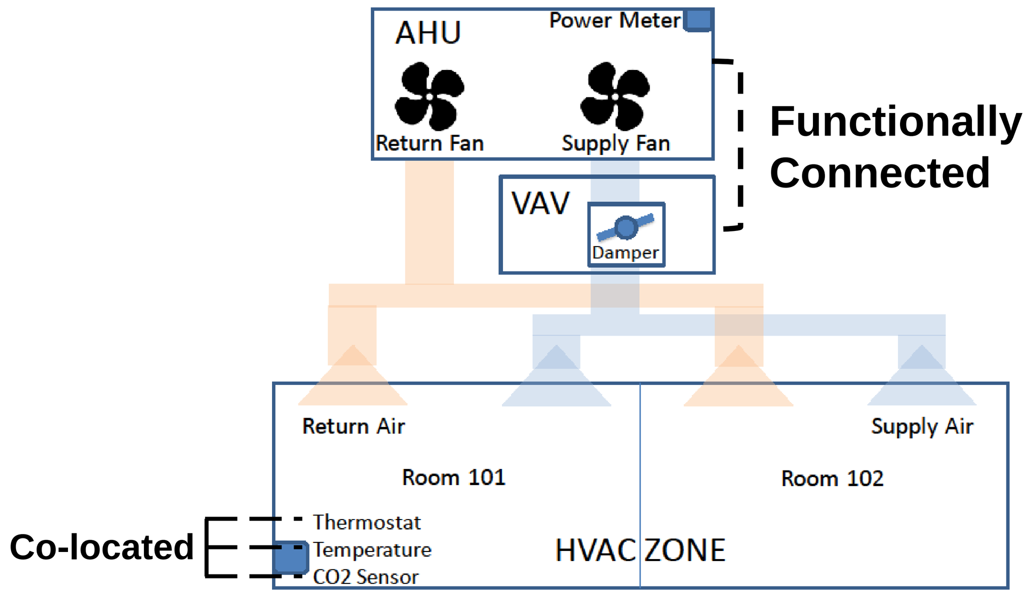
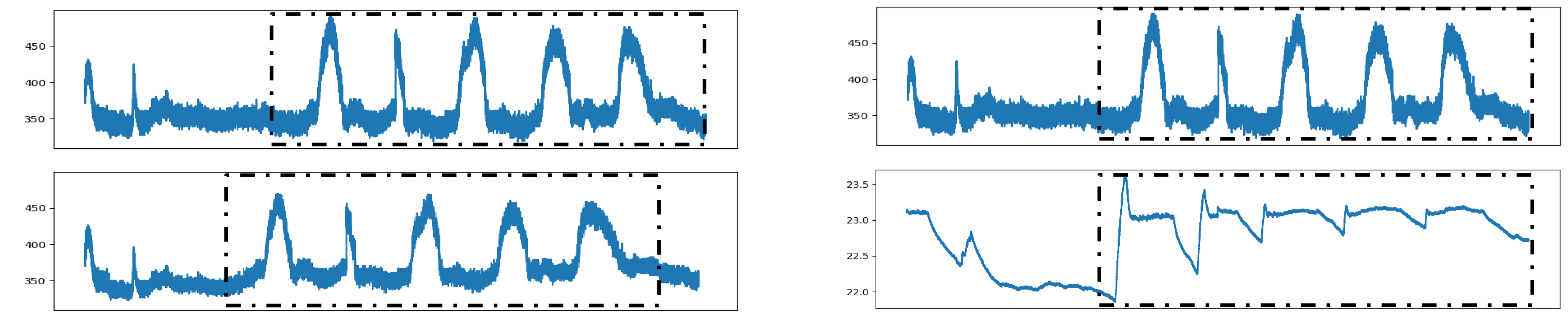
Introduction

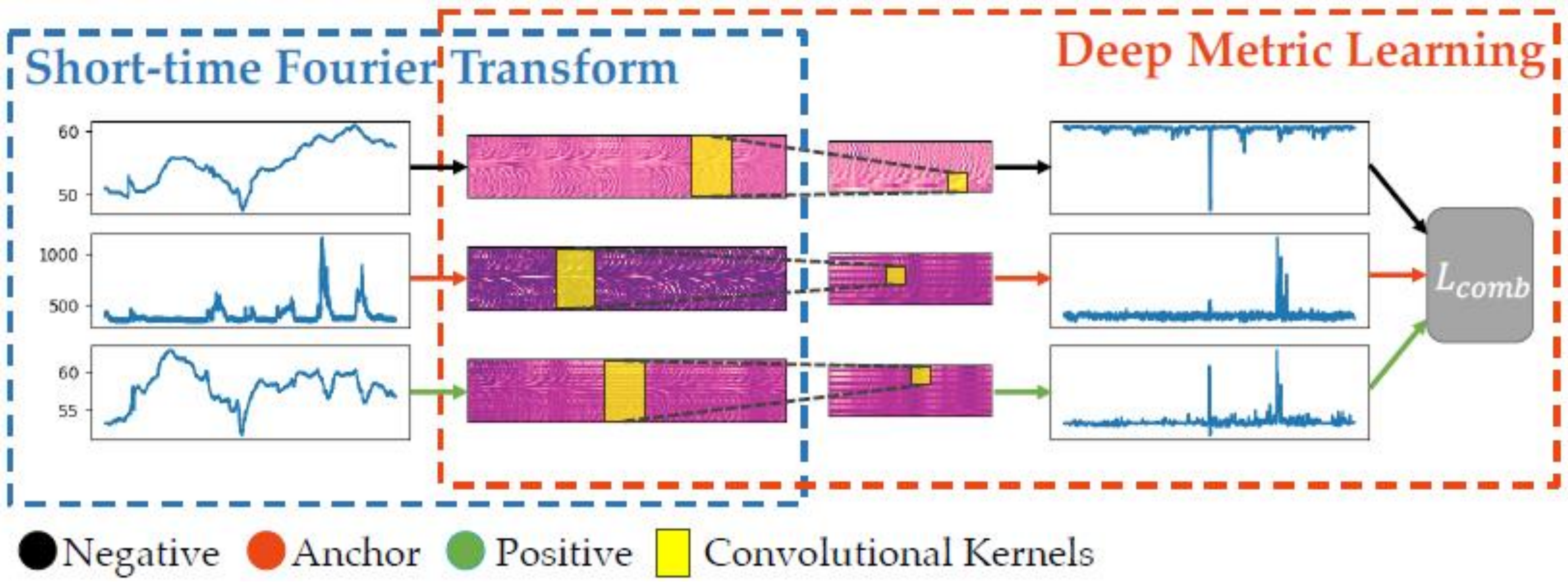


Related sensors are exposed to the same real-world events, thus exhibiting correlated changes in their sensor reading time series. However, 1) the event-triggered patterns are not synchronous and 2) the resulting changes can be distinct.



1) Room A & Room B: Asynchronous   2) CO2 & Temperature: Distinct Changes

Methodology



The input time series: $\mathbf{x} = \{x_1, x_2, \ldots, x_T\}$

Short-Time Fourier Transformation:

$$STFT^{(\tau,s)}\{\mathbf{x}\}(m,n) = \sum_{t=1}^{T} \mathbf{x}(t) \cdot \mathbf{w}(t - s \cdot m) \cdot e^{-j\frac{2\pi n}{\tau}(t - s\cdot m)}$$

Remove the direct current component and re-arrange the first k coefficients within a chunk into 2k frequency channels: a_1, b_1, a_2, b_2 … a_k, b_k, where a_n and b_n are the real and imaginary part of the n^{th} complex coefficient.

The output of STFT: $\mathbf{X} \in \mathbb{R}^{F\times N}$

The output of the neural networks: $\mathbf{y} = CNN(\mathbf{X})$

The loss function: $L_{comb}(\mathcal{T}) = L_{tri}(\mathcal{T}) + \lambda L_{ang}(\mathcal{T})$

$$L_{ang}(\mathcal{T}) = [||\mathbf{y}_a - \mathbf{y}_p||^2 - \mu||\mathbf{y}_c - \mathbf{y}_n||^2]_+ \quad L_{tri}(\mathcal{T}) = [||\mathbf{y}_a - \mathbf{y}_p||^2 - ||\mathbf{y}_a - \mathbf{y}_n||^2 + \gamma]_+$$

Results

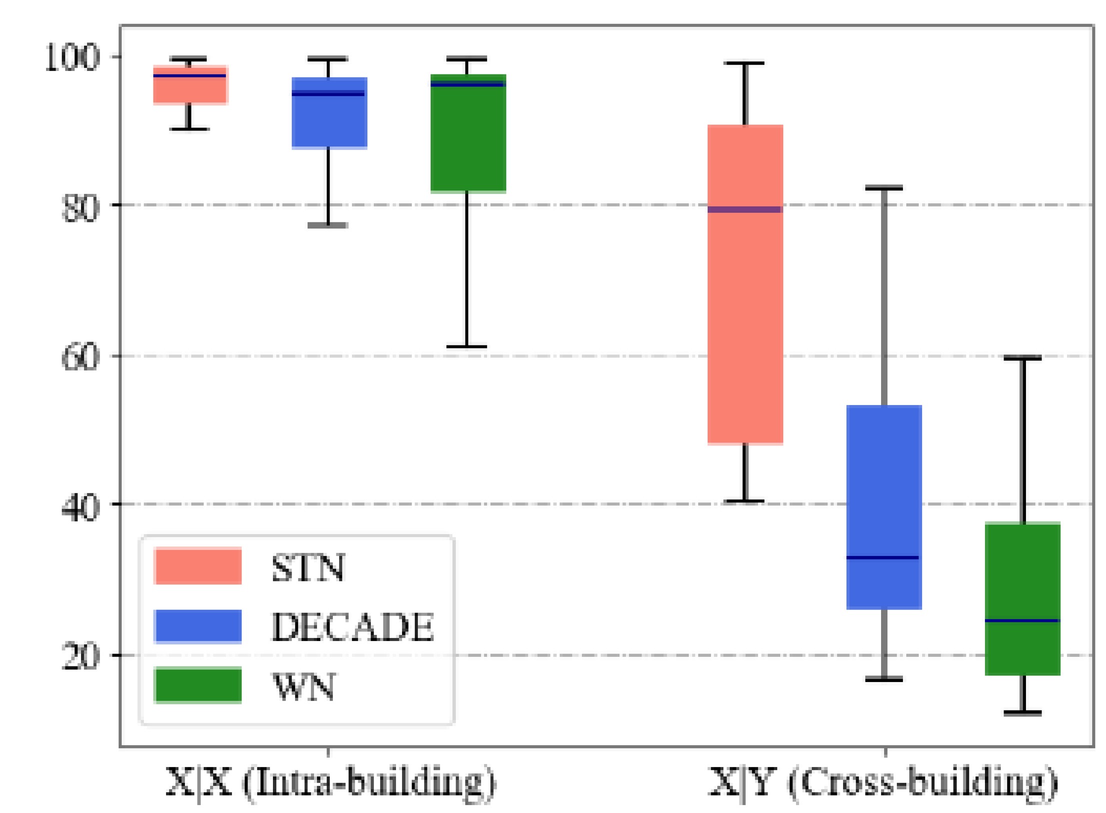
1. VAV assignment accuracy (%) for functional relation inference.

Building ID	10312	10320	10381	10596	10606	10642
Unsupervised						
HMM	18.01	11.50	25.64	21.02	31.59	34.75
MEMO	90.42	88.50	90.43	91.28	92.16	92.28
Supervised						
DTW	88.46	25.46	83.81	91.67	55.17	80.78
DECADE	96.54	77.27	93.33	**99.44**	85.98	96.08
WN	97.31	60.91	95.23	**99.44**	77.93	96.86
TN	97.30	42.73	96.19	93.33	52.18	96.07
SSN	97.69	42.73	95.24	97.78	63.67	93.72
STN	**98.07**	**90.00**	**96.23**	**99.44**	**93.10**	**98.03**

2. Accuracy (%) for spatial relation inference.

	Edge Accuracy	Room Accuracy
Unsupervised		
HMM	12.67	4.00
MEMO	19.00	10.00
Supervised		
DTW	37.27 ± 2.40	14.40 ± 2.94
DECADE	12.47 ± 1.61	2.00 ± 6.00
WN	17.47 ± 2.17	8.00 ± 9.80
TN	25.73 ± 1.94	6.00 ± 9.20
SSN	67.93 ± 8.66	50.20 ± 14.32
STN	**88.61 ± 2.08**	**80.00 ± 3.79**

3. Cross-building inference accuracy for functional relations across all six buildings: 'X|Y ' denotes training on Y and testing on X, and STN is our proposed method.



4. Functional inference accuracy under one-month v.s., ten-month training data.

	STN	WN	DECADE
One-month	47.27	26.36	30.90
Ten-month	90.00	60.91	77.27
Relative Drop (%)	47.48	56.72	60.01

5. VAV assignment accuracy using different sensor pairs. The left is the result of our model (STN) and the right is the result of MEMO.

VAV \ AHU	Supply AirPress	Supply AirTemp	Supply FanSpeed
AirFlowVolume	97.69/75.22	97.69/33.63	98.07/91.15
DischargeAirTemp	98.21/57.52	99.11/42.48	97.82/36.28
SpaceTemp	93.07/13.27	91.51/15.04	96.05/31.86