

EARTH: Accelerating Spatiotemporal Network K-function-based Analytics

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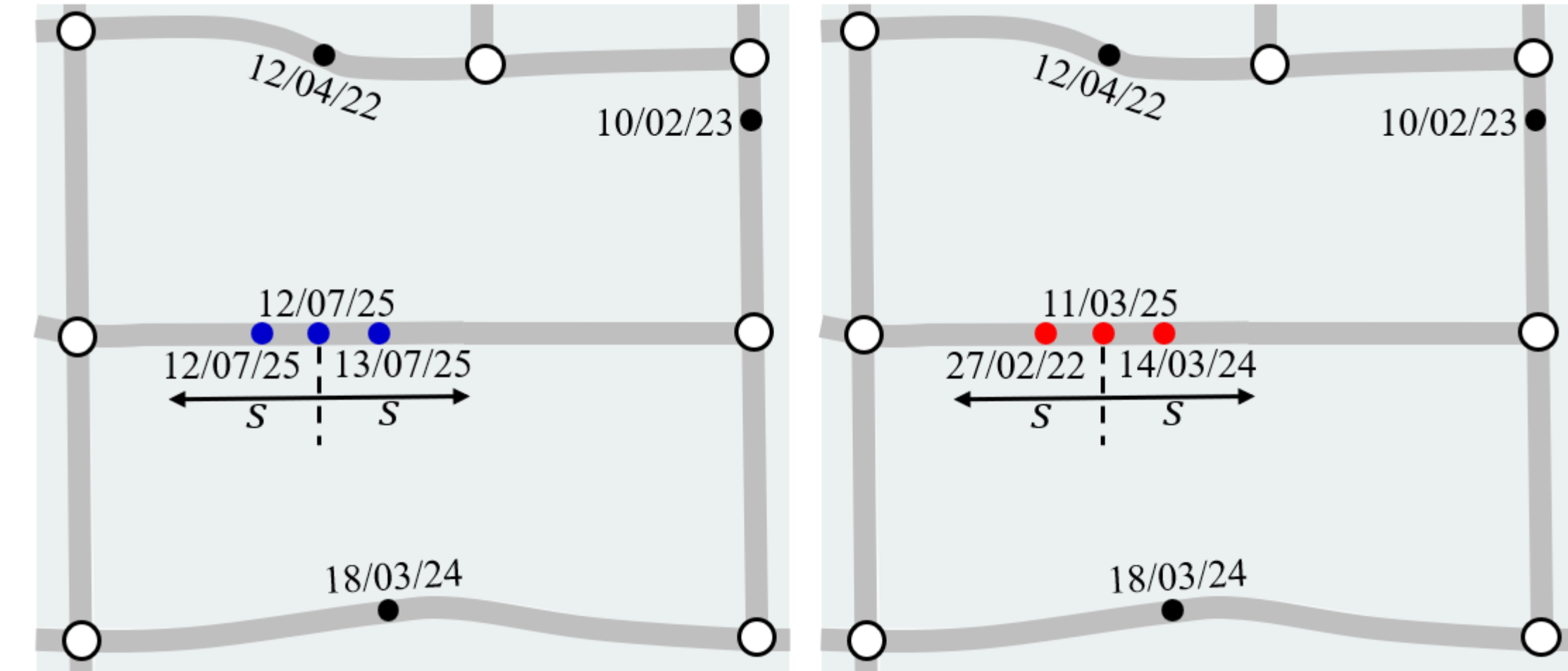
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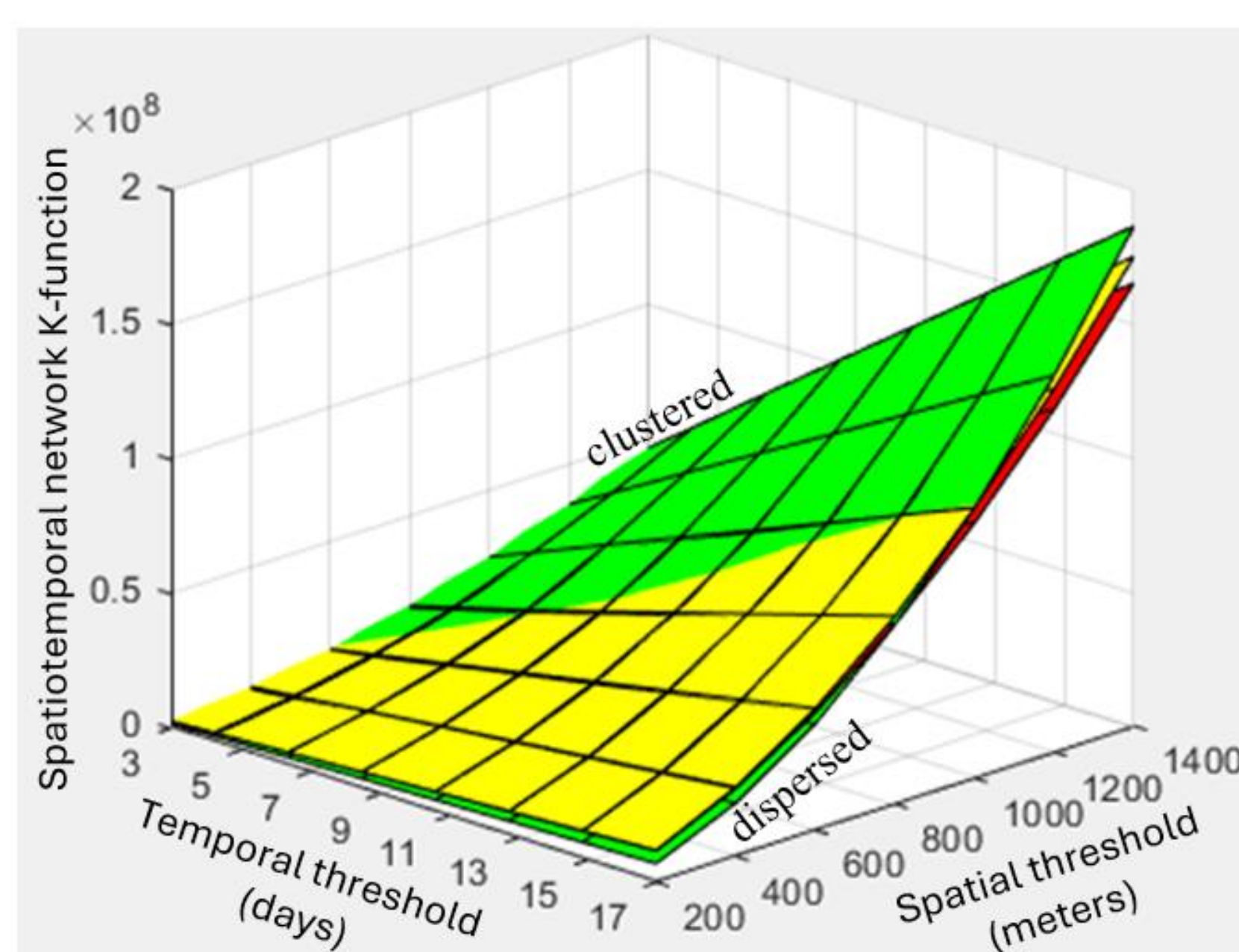


What is Spatiotemporal Network K-function-based Analytics?



(a) Dispersed

(b) Clustered



(c) Spatiotemporal network K-function plot

- Count the number of data points that are within the spatial threshold s and the temporal threshold t from each data point.

- Spatiotemporal network K-function:
 - A spatiotemporal dataset $P = \{(p_1, t_{p_1}), (p_2, t_{p_2}), \dots, (p_n, t_{p_n})\}$ with size n on a road network $G = (V, E)$
 - Spatial threshold s
 - Temporal threshold t

$$K_P(s, t) = \sum_{(p_i, t_{p_i}) \in P} \sum_{\substack{(p_j, t_{p_j}) \in P \\ j \neq i}} \mathbb{I}(d_G(p_i, p_j) \leq s, d(t_{p_i}, t_{p_j}) \leq t)$$

- Spatiotemporal network K-function plot:
 - A spatiotemporal dataset P and L randomly generated datasets $R_1, R_2, \dots, R_L$ (with the same size n)
 - M spatial thresholds $s_1, s_2, \dots, s_M$
 - T temporal thresholds $t_1, t_2, \dots, t_T$
 - Compute $K_P(s_\alpha, t_\beta)$ (green plane), $\mathcal{L}(s_\alpha, t_\beta)$ (red plane), and $\mathcal{U}(s_\alpha, t_\beta)$ (yellow plane)

$$\mathcal{L}(s_\alpha, t_\beta) = \min(K_{R_1}(s_\alpha, t_\beta), K_{R_2}(s_\alpha, t_\beta), \dots, K_{R_L}(s_\alpha, t_\beta))$$

$$\mathcal{U}(s_\alpha, t_\beta) = \max(K_{R_1}(s_\alpha, t_\beta), K_{R_2}(s_\alpha, t_\beta), \dots, K_{R_L}(s_\alpha, t_\beta))$$

Very Slow!

- Applications
 - Determine whether the spatiotemporal clusters/hotspots are meaningful.
 - Help for choosing the correct parameters for those statistical/clustering models.

Our Solution: EARTH

- Decomposition of $K_P(s, t)$

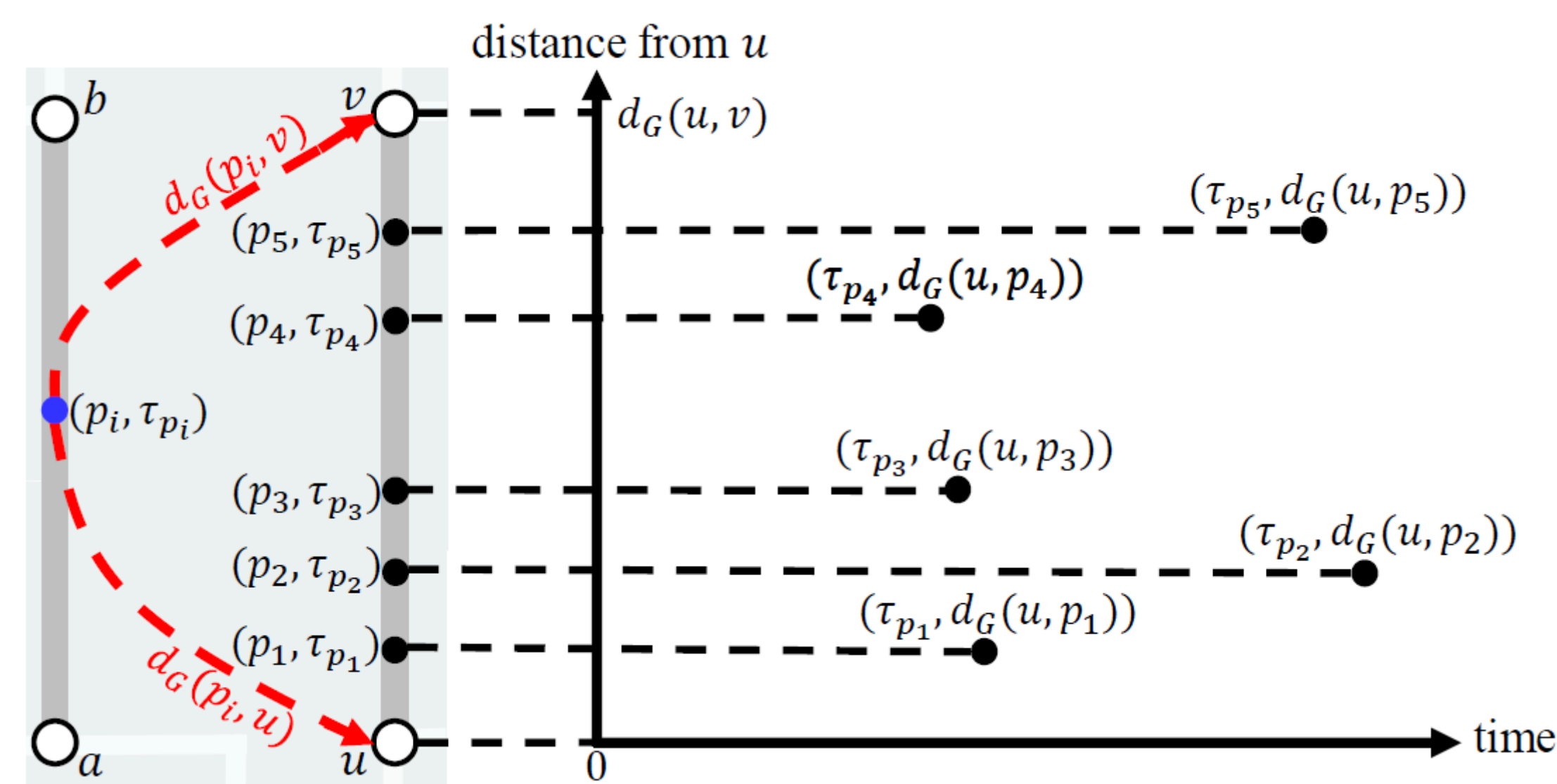
$$K_P(s, t) = \sum_{(p_i, t_{p_i}) \in P} \sum_{e \in E} C_{P(e)}^{(p_i, t_{p_i})}(s, t)$$

where

$$C_{P(e)}^{(p_i, t_{p_i})}(s, t) = \sum_{\substack{(p_j, t_{p_j}) \in P(e) \\ j \neq i}} \mathbb{I}(d_G(p_i, p_j) \leq s, d(t_{p_i}, t_{p_j}) \leq t)$$

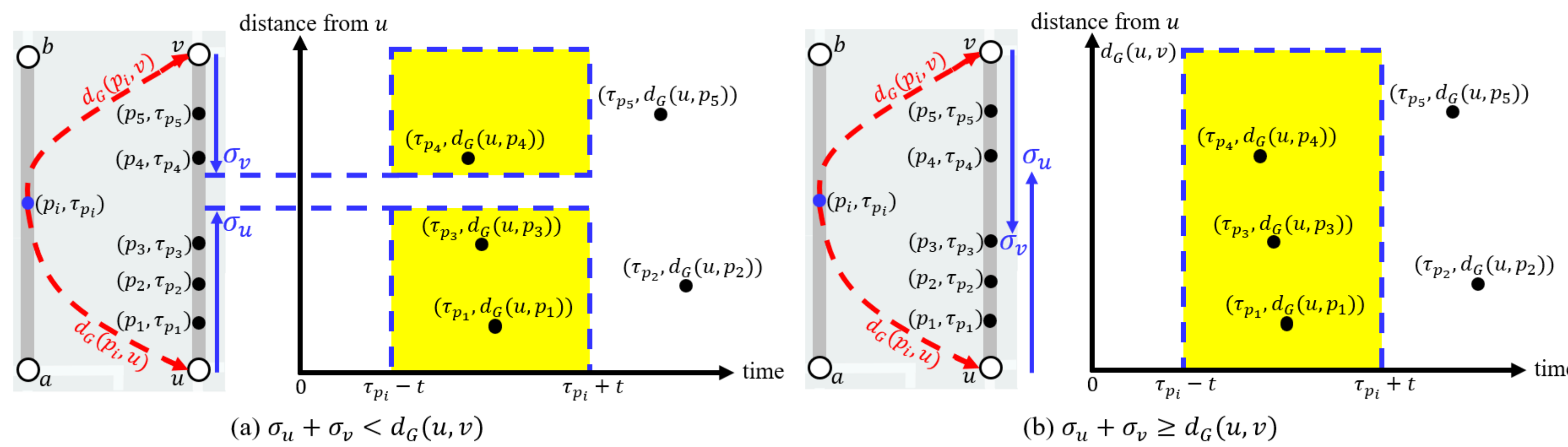
- Computing $C_{P(e)}^{(p_i, t_{p_i})}(s, t)$ takes $O(|P(e)|)$ time. $\otimes$

- Core idea: Mapping data points for each edge $e = (u, v)$ onto a two-dimensional (time, distance)-plane.



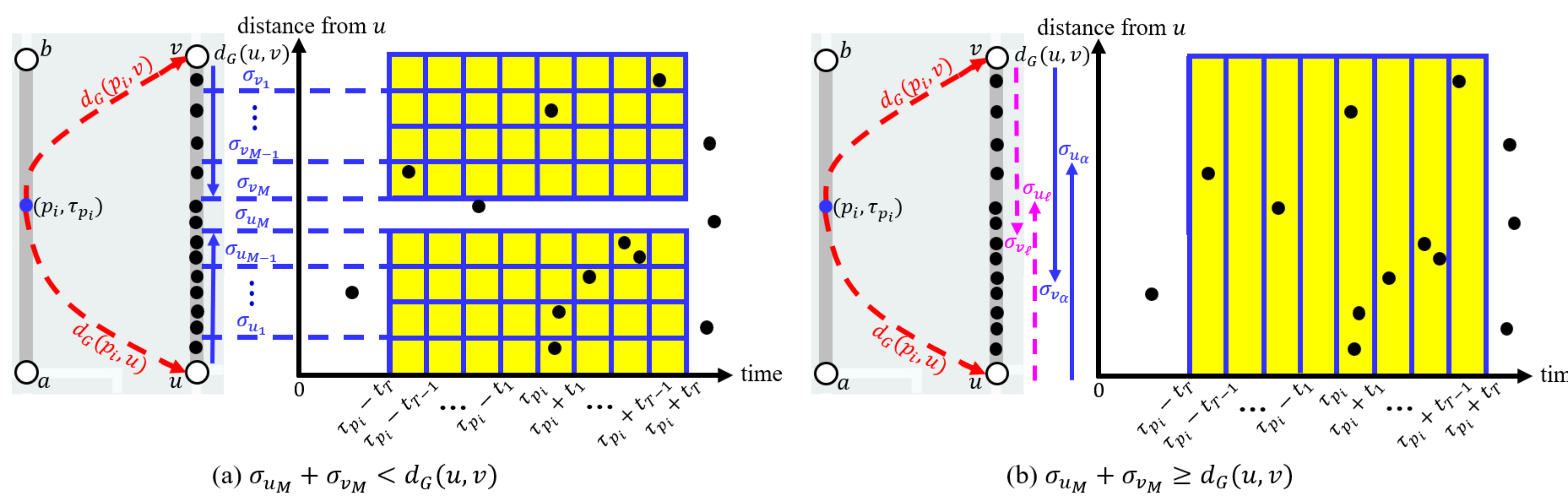
- Edge-Augmentation with Range-tree (EAR)

$O(\log |P(e)|)$ time $\odot$



- Multi-Threshold Sharing (MTS)

$O(MT + |P(e)|)$ time $\odot$



- EARTH = Edge-Augmentation with Range-tree + multi-THreshold sharing

Theoretical Performance

Experimental Results

Problem	Method	Time complexity	Space complexity
Spatiotemporal network K-function	RQS [54]	$O(n(\mathcal{T}_{SP} + n))$	$O(\mathcal{S}_{SP} + n)$
	SPS [55]	$O(E \mathcal{T}_{SP} + n^2)$	
	EAR (Section 4.1)	$O(E \mathcal{T}_{SP} + n E \log(\frac{n}{ E }) + n \log n)$	
Spatiotemporal network K-function plot	RQS [54]	$O(LMTn(\mathcal{T}_{SP} + n))$	$O(\mathcal{S}_{SP} + Ln + LMT)$
	SPS [55]	$O(LMT(E \mathcal{T}_{SP} + n^2))$	
	EAR (Section 4.1)	$O(E \mathcal{T}_{SP} + LMTn E \log(\frac{n}{ E }) + Ln \log n)$	$O(\mathcal{S}_{SP} + Ln + LMT)$ (Section 4.4)
	MTS (Section 4.2)	$O(E \mathcal{T}_{SP} + Ln^2 + LMTn E)$	
	EARTH (Section 4.3)	$O(E \mathcal{T}_{SP} + \min(LMTn E \log(\frac{n}{ E }) + Ln \log n, Ln^2 + LMTn E))$	

Name	n	$ V $	$ E $	Category	Ref.
Seattle	543,969	11,383	37,472	Crime events	[8]
London	822,382	19,984	75,609	Traffic accidents	[6]
New York	1,542,738	41,307	115,021	Traffic accidents	[3]
Los Angeles	2,108,154	35,933	109,708	Crime events	[2]

