

Large-scale Spatiotemporal Kernel Density Visualization



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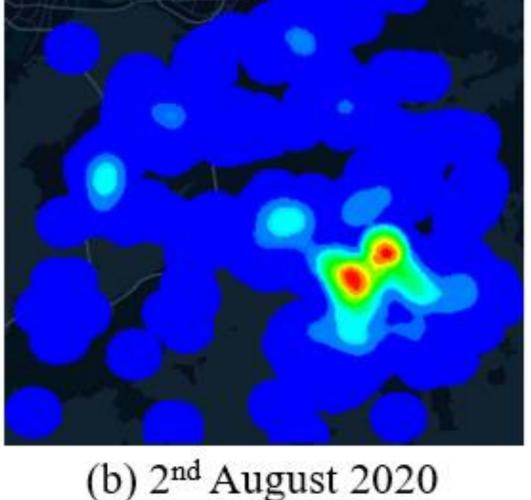
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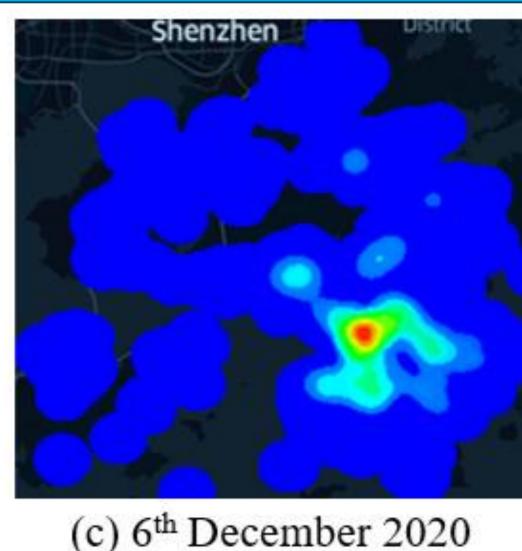
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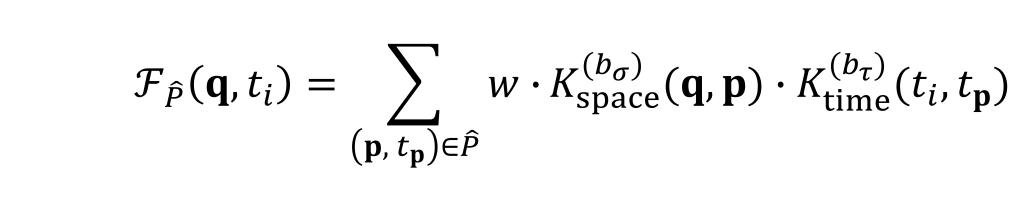


What is Spatiotemporal Kernel Density Visualization (STKDV)?







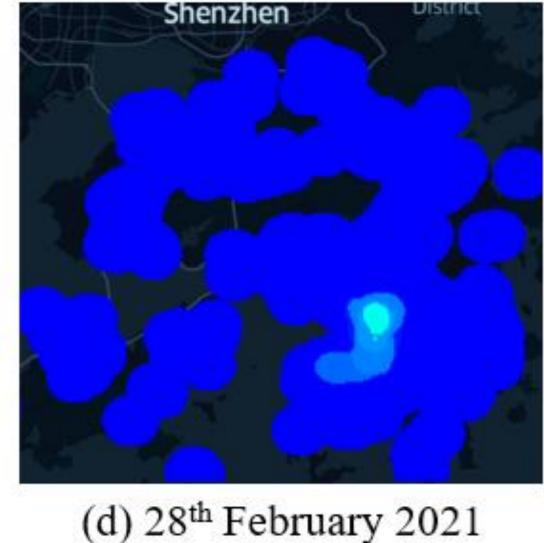


Commonly used spatial kernel functions and temporal kernel functions.

Color each pixel-timestamp (\mathbf{q}, t_i) pair based on the spatiotemporal

Uniform $\begin{cases} \frac{1}{b_{\sigma}} & \text{if } dist(\mathbf{q}, \mathbf{p}) \leq b_{\sigma} \\ 0 & \text{otherwise} \end{cases} \qquad \begin{cases} \frac{1}{b_{\tau}} & \text{if } dist(t_{i}, t_{\mathbf{p}}) \leq b_{\tau} \\ 0 & \text{otherwise} \end{cases}$ Epanechnikov $\begin{cases} 1 - \frac{1}{b_{\sigma}^{2}} dist(\mathbf{q}, \mathbf{p})^{2} & \text{if } dist(\mathbf{q}, \mathbf{p}) \leq b_{\sigma} \\ 0 & \text{otherwise} \end{cases} \qquad \begin{cases} 1 - \frac{1}{b_{\tau}^{2}} dist(t_{i}, t_{\mathbf{p}})^{2} & \text{if } dist(t_{i}, t_{\mathbf{p}}) \leq b_{\tau} \\ 0 & \text{otherwise} \end{cases}$ $\begin{cases} (1 - \frac{1}{b_{\tau}^{2}} dist(\mathbf{q}, \mathbf{p})^{2})^{2} & \text{if } dist(\mathbf{q}, \mathbf{p}) \leq b_{\sigma} \\ 0 & \text{otherwise} \end{cases} \qquad \begin{cases} (1 - \frac{1}{b_{\tau}^{2}} dist(t_{i}, t_{\mathbf{p}})^{2})^{2} & \text{if } dist(t_{i}, t_{\mathbf{p}}) \leq b_{\tau} \\ 0 & \text{otherwise} \end{cases}$	Kernel	$K_{ ext{space}}^{(b_{\sigma})}(\mathbf{q},\mathbf{p})$	$K_{ ext{time}}^{(b_{ au})}(t_i,t_{f p})$	
otherwise	Uniform	· · · · · · · · · · · · · · · · · · ·	l	
$\int \left(1 - \frac{1}{b^2} dist(\mathbf{q}, \mathbf{p})^2\right)^2 \text{if } dist(\mathbf{q}, \mathbf{p}) \leq b_{\sigma} \int \left(1 - \frac{1}{b^2} dist(t_i, t_{\mathbf{p}})^2\right)^2 \text{if } dist(t_i, t_{\mathbf{p}}) \leq b_{\tau}$	Epanechnikov		· '	
Quartic $\begin{cases} 0 & \sigma \\ 0 & \text{otherwise} \end{cases}$ otherwise	Quartic	$\begin{cases} \left(1 - \frac{1}{b_{\sigma}^2} dist(\mathbf{q}, \mathbf{p})^2\right)^2 & \text{if } dist(\mathbf{q}, \mathbf{p}) \le b_{\sigma} \\ 0 & \text{otherwise} \end{cases}$	$\begin{cases} \left(1 - \frac{1}{b_{\tau}^2} dist(t_i, t_{\mathbf{p}})^2\right)^2 & \text{if } dist(t_i, t_{\mathbf{p}}) \le b_{\tau} \\ 0 & \text{otherwise} \end{cases}$	

(a) Hong Kong COVID-19 cases



(e) 28th January 2022

Detect the disease outbreak based on the Hong Kong COVID-19 location dataset.

STKDV is computationally expensive, which takes O(XYTn) time.

Example:

- The resolution size $(X \times Y)$: 128×128
- The number of timestamps (T): 128

kernel density function $\mathcal{F}_{\widehat{P}}(\mathbf{q},t_i)$, where

- The total number of data points (n): 1,000,000
- The total cost is: 2.09 trillion operations ©

Overview of Existing Solution (SWS)

$W(t_i)$ $(\mathbf{p}, t_{\mathbf{p}})$ (\mathbf{q},t_i)

Only those data points $(\mathbf{p}, t_{\mathbf{p}})$ in $W(t_i)$

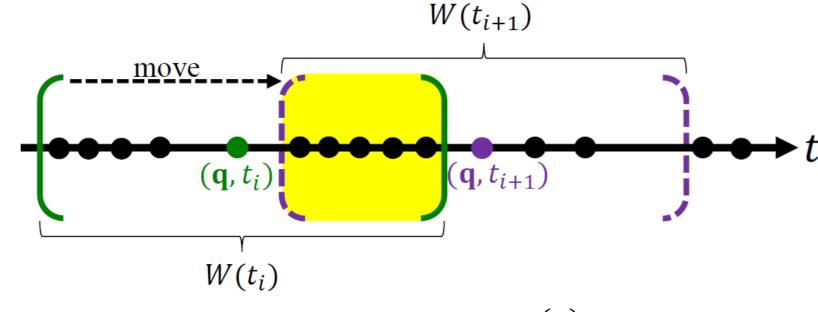
 $= \sum_{(\mathbf{p}, t_{\mathbf{p}}) \in \widehat{P}} w \cdot K_{\text{space}}^{(b_{\sigma})}(\mathbf{q}, \mathbf{p}) \cdot \left(1 - \frac{1}{b_{\tau}^{2}} dist(t_{i}, t_{\mathbf{p}})^{2}\right)$

where $S_{W(t_i)}^{(u)}(\mathbf{q}) = \sum_{(\mathbf{p},t_{\mathbf{p}})\in W(t_i)} t_{\mathbf{p}}^u \cdot K_{\text{space}}^{(b_\sigma)}(\mathbf{q},\mathbf{p})$

 $= w \left(1 - \frac{t_i^2}{b_\tau^2}\right) S_{W(t_i)}^{(0)}(\mathbf{q}) + \frac{2wt_i}{b_\tau^2} S_{W(t_i)}^{(1)}(\mathbf{q}) - \frac{w}{b_\tau^2} S_{W(t_i)}^{(2)}(\mathbf{q})$

can contribute to $\mathcal{F}_{\widehat{P}}(\mathbf{q}, t_i)$.

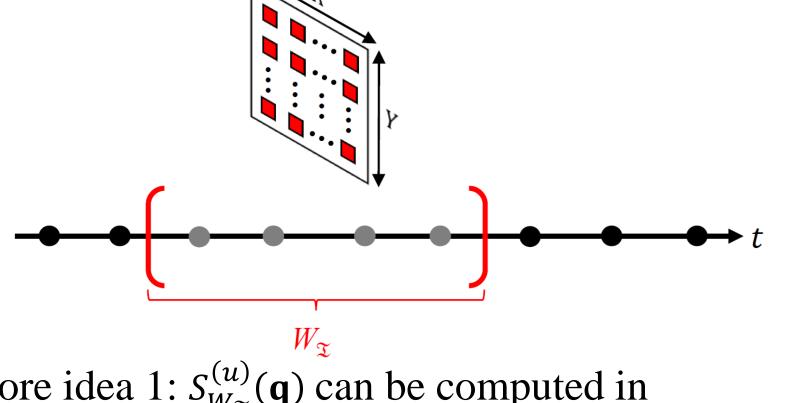
 $\mathcal{F}_{\widehat{P}}(\mathbf{q},t_i)$



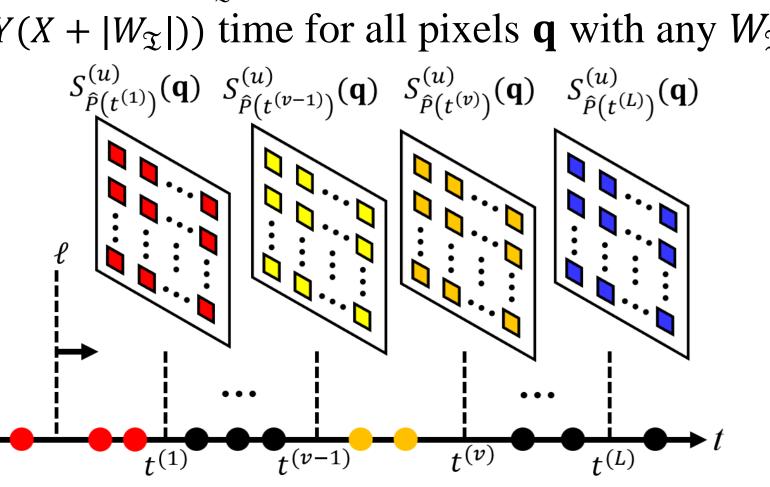
Efficiently update from $S_{W(t_i)}^{(u)}(\mathbf{q})$ to $S_{W(t_{i+1})}^{(u)}(\mathbf{q})$.

The time complexity of SWS is O(XY(T+n)).

Core ideas of Our Solution (PREFIX) $S_{\hat{P}(\mathcal{U})}^{(u)}(\mathbf{q})$



Core idea 1: $S_{W_{\tau}}^{(u)}(\mathbf{q})$ can be computed in $O(Y(X + |W_{\mathfrak{T}}|))$ time for all pixels **q** with any $W_{\mathfrak{T}}$.



Core idea 2: Takes O(XY) time to obtain $S_{W_{\mathfrak{I}}}^{(u)}(\mathbf{q})$, where

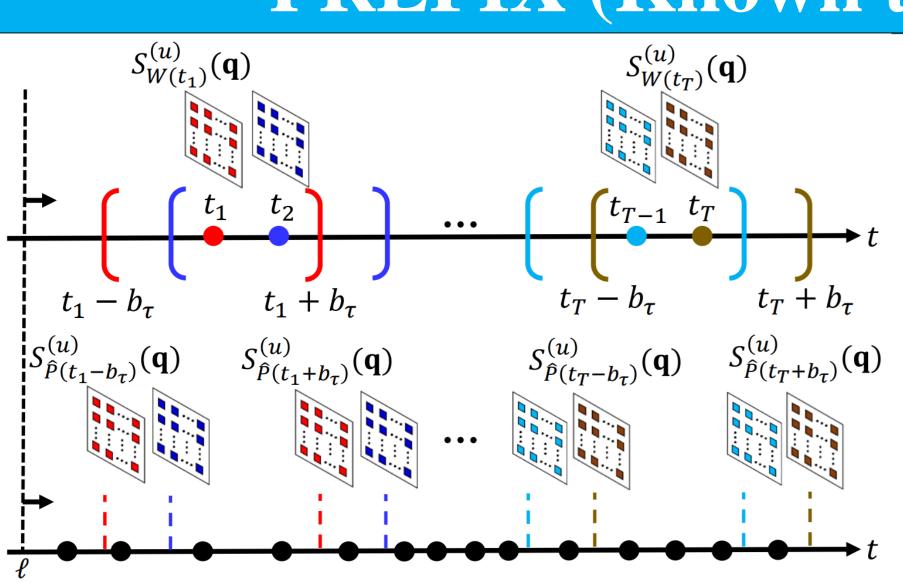
$$S_{W_{\mathfrak{T}}}^{(u)}(\mathbf{q}) = S_{\widehat{P}(\mathcal{U})}^{(u)}(\mathbf{q}) - S_{\widehat{P}(\mathcal{L})}^{(u)}(\mathbf{q})$$

Core idea 3: Takes O(XYL + Yn) time for maintaining statistical matrices for *L* timestamps.

PREFIX (On-the-fly timestamps)

Set $W_{\mathfrak{T}}$ to be $W(t_i)$ in Core idea 1. Compute $S_{W(t_i)}^{(u)}(\mathbf{q})$ for all pixels \mathbf{q} in O(Y(X+n)) time \odot (\mathbf{q},t_i) The time complexity of PREFIX is O(Y(X+n)) \odot $W(t_i)$

PREFIX (Known timestamps)



Computing the statistical matrices for all 2T prefix sets is O(XYT + Yn) time (by setting L = 2T in Core idea 3).

Since there are T windows, we can compute $S_{W(t_i)}^{(u)}(\mathbf{q})$ for all pixels \mathbf{q} in O(XYT) time. (based on Core idea 2).

The time complexity of PREFIX is O(XYT + Yn) ©

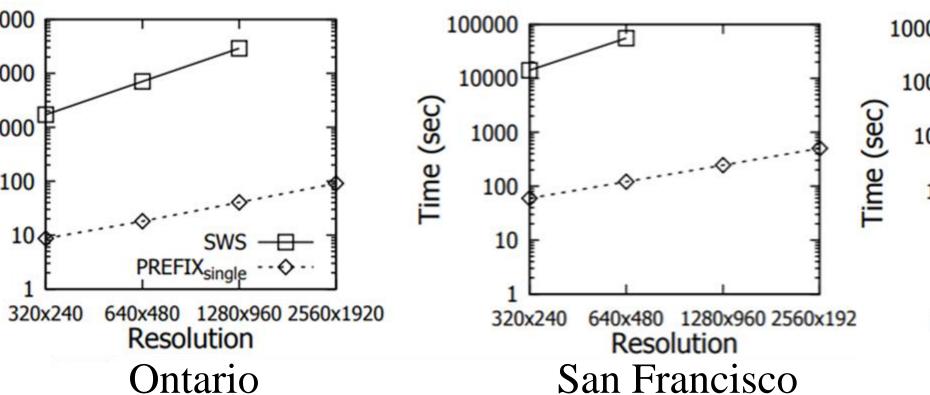
Theoretical Results

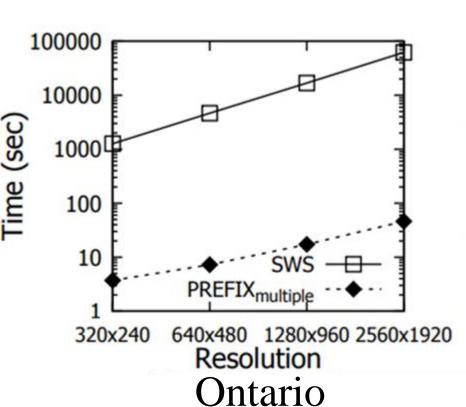
Problem	Method	Time complexity	Space complexity
STKDV	SWS	O(XYn)	O(XY+n)
(on-the-fly	PREFIXsingle	O(Y(X+n))	O(XY+n)
timestamp)	(Section IV-B)	(Theorem 1)	(Theorem 4)
STKDV	SWS	O(XY(T+n))	O(XYT+n)
	PREFIX _{multiple}	O(XYT + Yn)	O(XYT+n)
timestamps)	(Section IV-C)	(Theorem 2)	(Theorem 5)
	SWS	O(MNXY(T+n))	O(MNXYT+n)
Bandwidth	PREFIX _{tuning}	O(M(XYTN + Yn))	O(MNXYT+n)
tuning	(Section IV-D)	(Theorem 3)	(Theorem 6)

100000 10000 1000 1000

Resolution

Ontario





Experimental Results

