

## Coresets for $(k, \ell)$ -Median under Dynamic Time Warping

**Jacobus Conradi** , Benedikt Kolbe, Ioannis Psarros, Dennis Rohde



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EuroCG'24, Ioannina

## Prelude

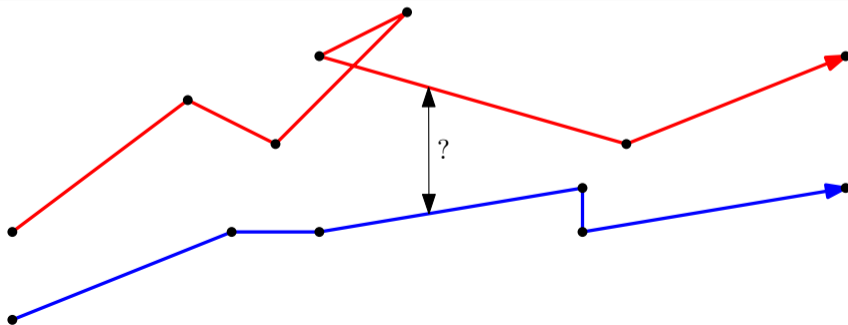
### The key players

## Key player I – curves of complexity $\leq m$

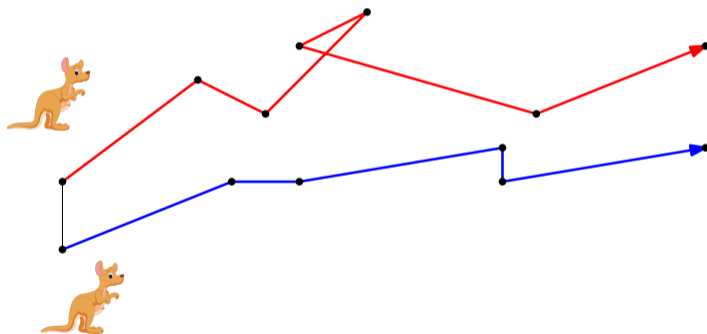
Central objects  $\mathbb{X}_m^d$  and dtw

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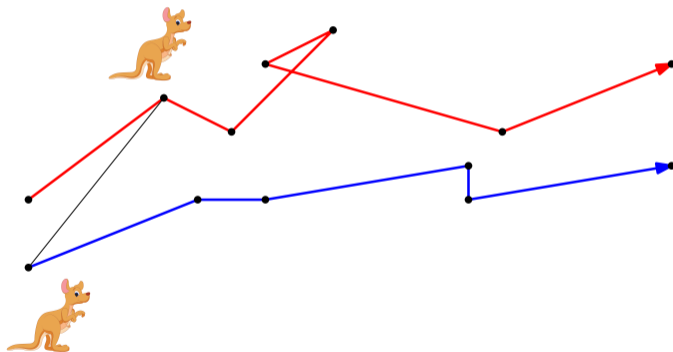


# Dynamic Time Warping



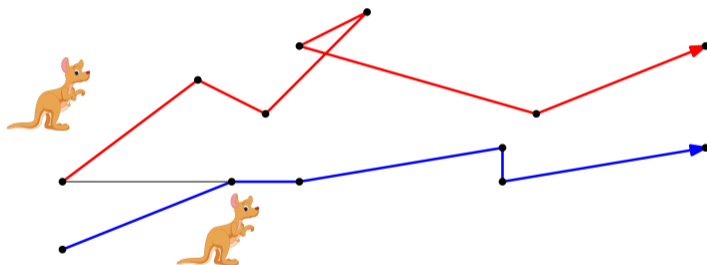
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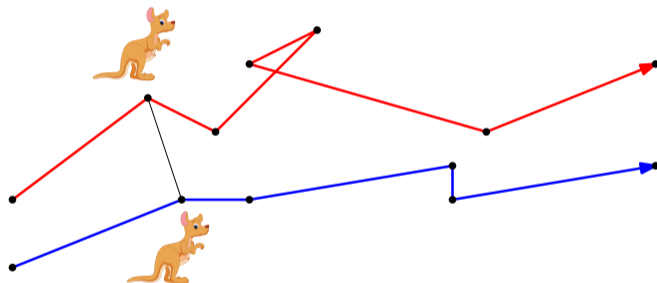
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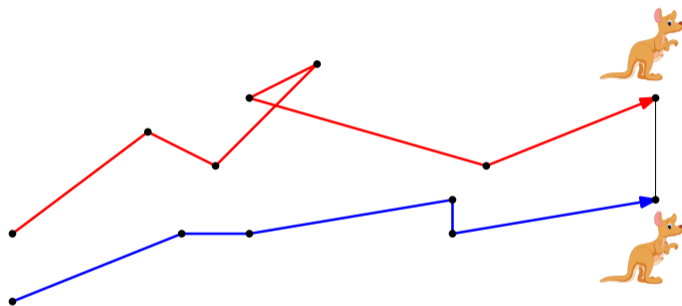
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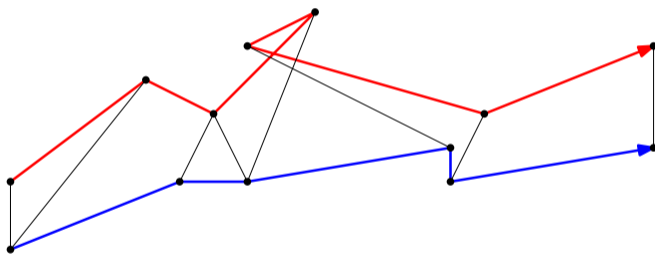
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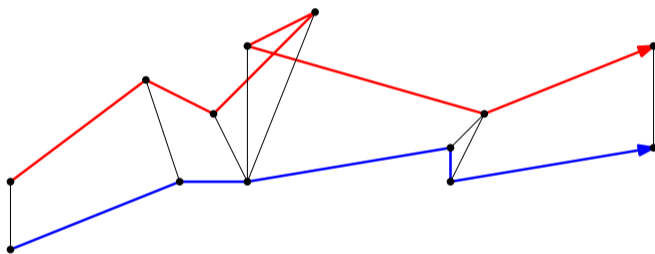


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**joint traversals:** Each kangaroo allowed to hop either one step ahead, or stay put.

**dtw:** minimal possible sum of Euclidean distances.

## Key player I – curves of complexity $\leq m$ under dtw

### Central objects $\mathbb{X}_m^d$ and dtw

Complexity  $\leq m$  (polygonal) **curves** in  $\mathbb{X}_m^d$ : point sequences  $\tau = (\tau_1, \dots, \tau_{m'})$  with  $\tau_i \in \mathbb{R}^d$  and  $m' \leq m$ .

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### Definition ( DTW)

Let  $\sigma = (\sigma_1, \dots, \sigma_m) \in \mathbb{X}_{=m}^d, \tau = (\tau_1, \dots, \tau_\ell) \in \mathbb{X}_{=\ell}^d$ . The DTW of  $\sigma$  and  $\tau$  is

$$\text{dtw}(\sigma, \tau) = \min_{T \in \mathcal{T}_{m,\ell}} \sum_{(i,j) \in T} \|\sigma_i - \tau_j\|_2$$

- ▶ dtw less sensitive to outliers than Fréchet **but** not a metric
- ▶  $\text{dtw}_p \xrightarrow{p \rightarrow \infty} d_{\text{discrete Fréchet}}$ ;  $\text{dtw}_1 = \text{dtw}$

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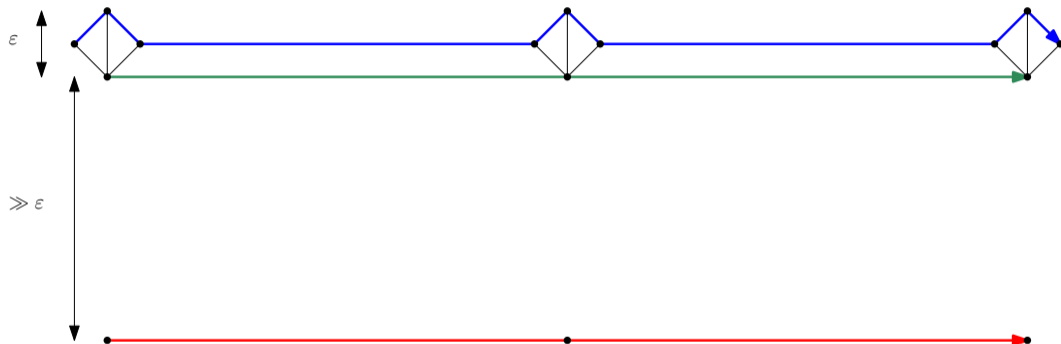
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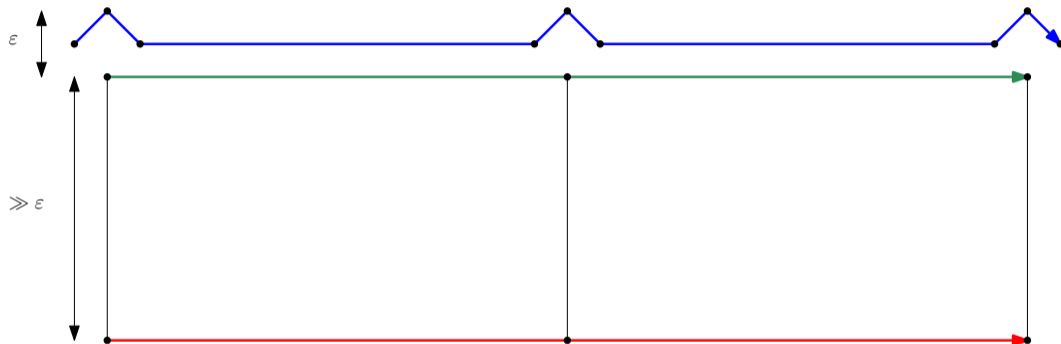
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## Violated triangle inequality



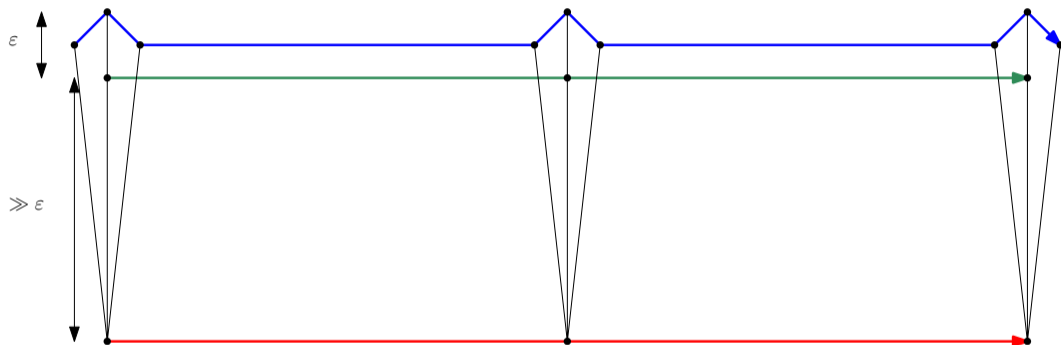
$$\text{dtw}(\blacksquare, \blacksquare) \approx 9\epsilon$$

## Violated triangle inequality



$$\text{dtw}(\blacksquare, \blacksquare) \approx 3$$

## Violated triangle inequality



$$\text{dtw}(\blacksquare, \blacksquare) \approx 9 \text{ but } 9 \not\leq 3 + 9\epsilon$$

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## $k$ -median problem for curves

$(k, \ell)$ -median problem for  $\mathbb{X}_m^d$  and  $k, \ell \in \mathbb{N}$ :

Given a set of  $n \in \mathbb{N}$  curves  $T = \{\tau_1, \dots, \tau_n\} \subset \mathbb{X}_m^d$ , identify  $k$  center curves  $C = \{c_1, \dots, c_k\} \subset \mathbb{X}_\ell^d$  that minimize  $\text{cost}(T, C) = \sum_{\tau \in T} \min_{c \in C} \text{dtw}_p(\tau, c)$ .

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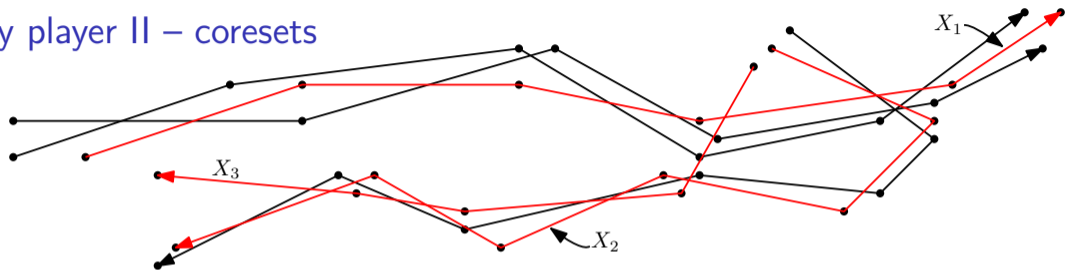
Definition ( $(\alpha, \beta)$ -approximation for  $(k, \ell)$ -median)

A set  $\hat{C} \subset \mathbb{X}_\ell^d$  is an  $(\alpha, \beta)$ -approximation of  $(k, \ell)$ -median if  $|\hat{C}| \leq \beta k$  and

$$\text{cost}(T, \hat{C}) \leq \alpha \text{cost}(T, C) = \alpha \sum_{\tau \in T} \min_{c \in C} \text{dtw}_p(\tau, c)$$

for any  $C \subset \mathbb{X}_\ell^d$  of size  $k$ .

## Key player II – coresets



### Definition ( $\epsilon$ -coreset)

Let  $T \subset \mathbb{X}_m^d$  and  $\epsilon \in (0, 1)$ . A weighted multiset  $S \subset \mathbb{X}_m^d$  with weights  $w : S \rightarrow \mathbb{R}_{>0}$  is a  **$\epsilon$ -coreset** for  $(k, \ell)$ -median of  $T$  under  $\text{dtw}_p$  if  $\forall C \subset \mathbb{X}_\ell^d$  with  $|C| = k$

$$(1 - \epsilon) \text{cost}(T, C) \leq \sum_{s \in S} w(s) \min_{c \in C} \text{dtw}_p(s, c) \leq (1 + \epsilon) \text{cost}(T, C).$$

## Part I

Sensitivity-sampling

or

Identifying our problems

## Sensitivity ( $\hat{=}$ importance) sampling

Framework for  $\epsilon$ -coreset for  $k$ -median in metric spaces [Feldman, Langberg'11, Braverman, Feldman, Lang'16,...]

- ▶ If there is a  $(\alpha, \beta)$ -approximation algorithm and
- ▶ If the metric space has VC dimension  $\rho$
- ▶ Then we can sample a coreset of size roughly  $\tilde{O}(\epsilon^{-2} \alpha \beta k \rho \log(n))$

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- ▶ No known polynomial  $(\alpha, \beta)$ -approximation algorithm for  $(k, \ell)$ -median
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### Theorem (C, Kolbe, Psarros, Rohde)

There is a distance  $\widetilde{\text{dtw}}_p$  with  $\text{dtw}_p \leq \widetilde{\text{dtw}}_p \leq (1 + \epsilon) \text{dtw}_p$ . Its associated ball range space has VC dimension  $O(d\ell \log(\ell m \epsilon^{-1}))$ .

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## Part II

$(\alpha, \beta)$ -approximations of  $(k, \ell)$ -median

or

How to force DTW to be a metric

## The iterated triangle inequality

### Lemma (Iterated triangle inequality)

Let  $s \in \mathbb{X}_\ell^d$ ,  $t \in \mathbb{X}_{\ell'}^d$  and  $X = (x_1, \dots, x_r)$  be any ordered set of curves in  $\mathbb{X}_m^d$ . Then

$$\text{dtw}_p(s, t) \leq (\ell + \ell')^{1/p} \left( \text{dtw}_p(s, x_1) + \sum_{i < r} \text{dtw}_p(x_i, x_{i+1}) + \text{dtw}_p(x_r, t) \right).$$

- ▶ No dependence on complexities of visited curves
- ▶ Connection to empirical observation that the  $\Delta$ -inequality is only rarely violated

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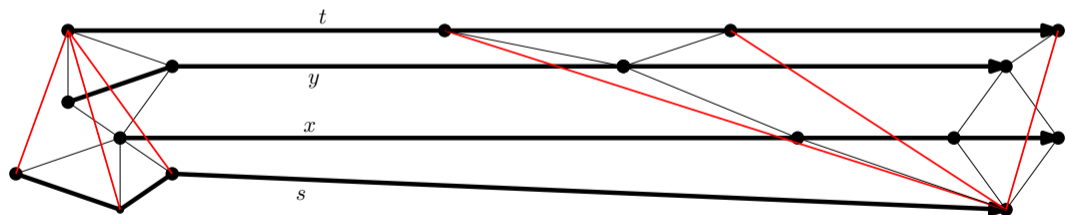
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# The iterated triangle inequality illustrated

## Key observation

Proof of  $\Delta$ -inequality boils down to constructing some traversal between the end curves  $s$  and  $t$  from optimal traversals for the inbetween curves.



## Bridging the gap to a metric space

### Consequences of iterated $\Delta$ -inequality

- ▶ Shortest path from  $\sigma$  to  $\tau$  in  $\mathcal{T}$  not necessarily direct edge between them
- ▶ However, the direct edge is not too far off
- ▶ Defining  $\overline{\text{dtw}_p |_{\mathcal{T}}}$  to be the **metric closure** (shortest path metric), we have

$$\overline{\text{dtw}_p |_{\mathcal{T}}} \leq \text{dtw}_p |_{\mathcal{T}} \leq (2m)^{1/p} \overline{\text{dtw}_p |_{\mathcal{T}}} \leq (2m)^{1/p} \text{dtw}_p |_{\mathcal{T}}$$

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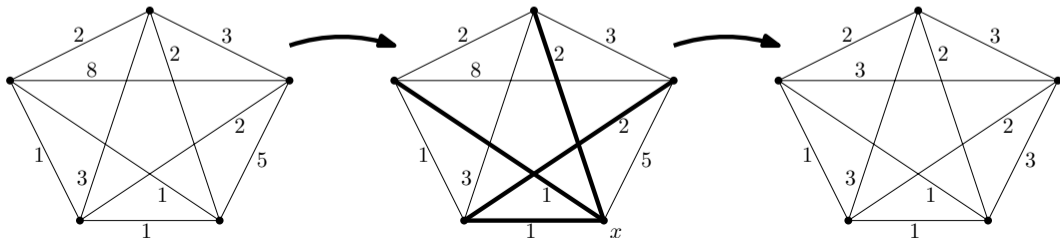
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## Denouement - putting it all together

We can now access the wealth of  $k$ -median results in metric spaces:

Theorem (C, Kolbe, Psarros, Rohde)

*We can compute a  $(O((1 + \epsilon)(m\ell)^{1/p}), 4)$ -approximation for  $(k, \ell)$ -median in  $\mathbb{X}_m^d$  in time*

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Theorem (C, Kolbe, Psarros, Rohde)

*Given a set  $T \subset \mathbb{X}_m^d$  ( $|T| = n$ ), sensitivity sampling yields an  $\epsilon$ -coreset for  $(k, \ell)$ -median on  $T$  of size (hiding other log factors)*

$$\tilde{O}(\epsilon^{-2} d \ell k^2 (m\ell)^{2/p} \log(n)).$$

## Take-home message

- ▶ DTW – widespread similarity measure for trajectories;  
not a metric, but not too far off
- ▶ We find new  $(\alpha, \beta)$ -approximations from approximating DTW by a path metric
- ▶ We obtain bounds on the VC dimension of  $\text{dtw}_p$  that allow coresets constructions from approximations to  $(k, \ell)$ -median

## Take-home message

- ▶ DTW – widespread similarity measure for trajectories;  
not a metric, but not too far off
- ▶ We find new  $(\alpha, \beta)$ -approximations from approximating DTW by a path metric
- ▶ We obtain bounds on the VC dimension of  $\text{dtw}_p$  that allow coresets constructions from approximations to  $(k, \ell)$ -median

Thanks for your attention!  
Questions?

## Main references

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