Times Series Alignment on Incomparable Spaces

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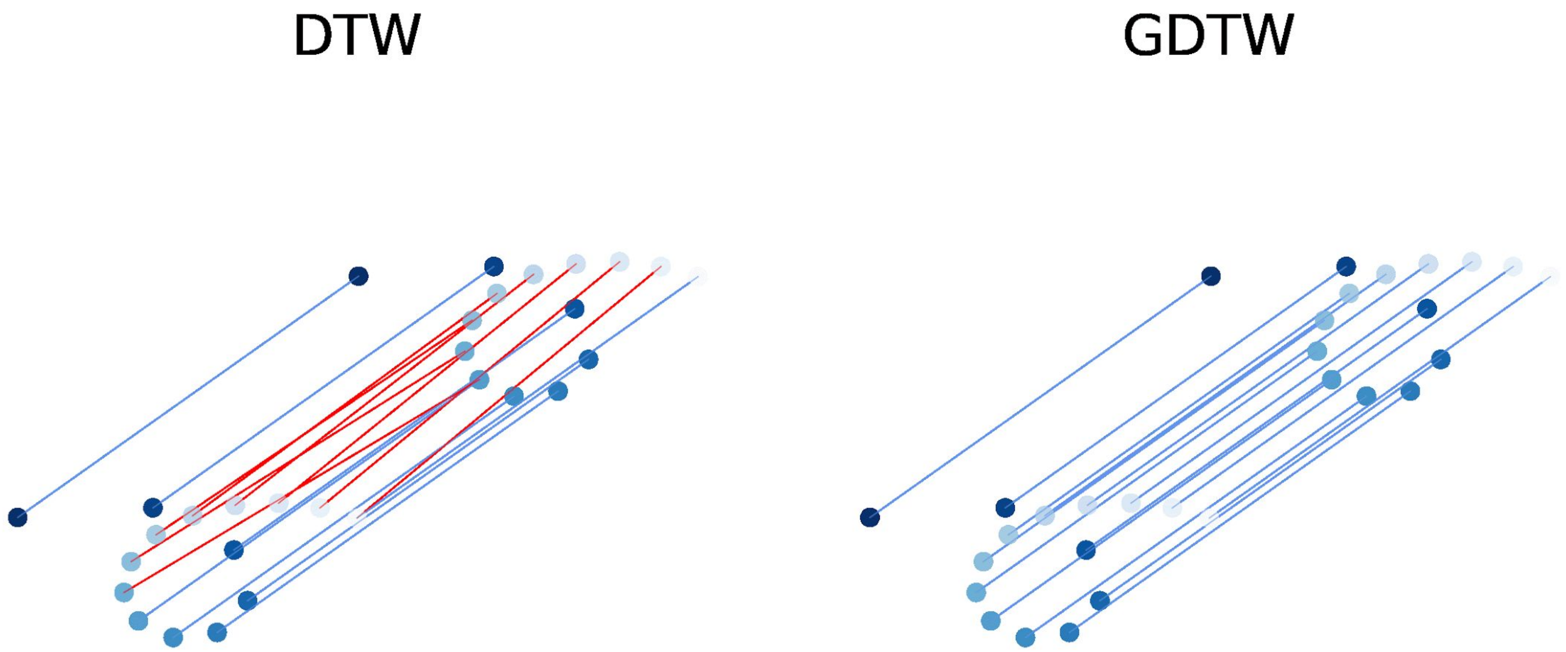
Goal 1: Heterogenous Alignments

Euclidean Points

Pixel Images

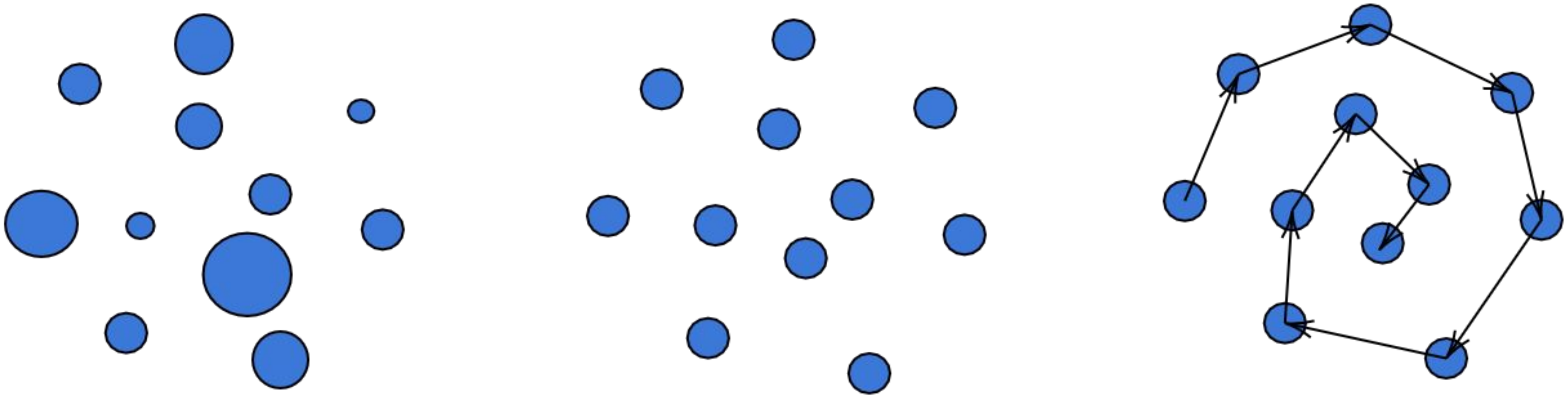
- Goal: temporal alignments between time series from different modalities

Goal 2: Invariant Alignments



- Goal: temporal alignments invariant to isometries (rotations, translations,...)

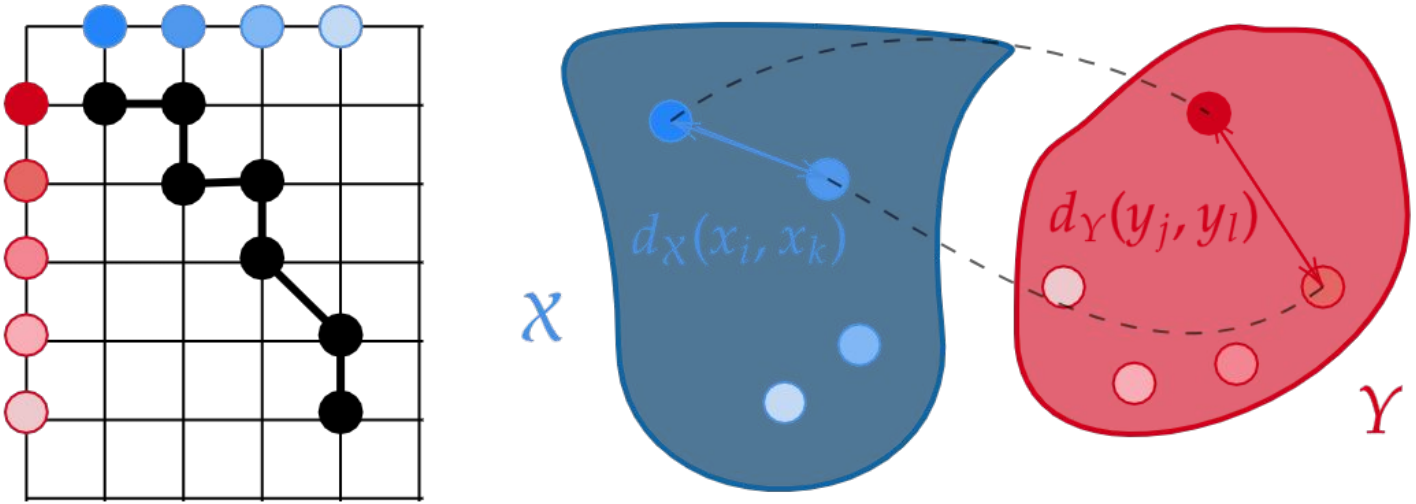
Connecting Optimal Transport with Time Series



- Time series: discrete probability measures with an ordering

Introducing Gromov Dynamic Time Warping

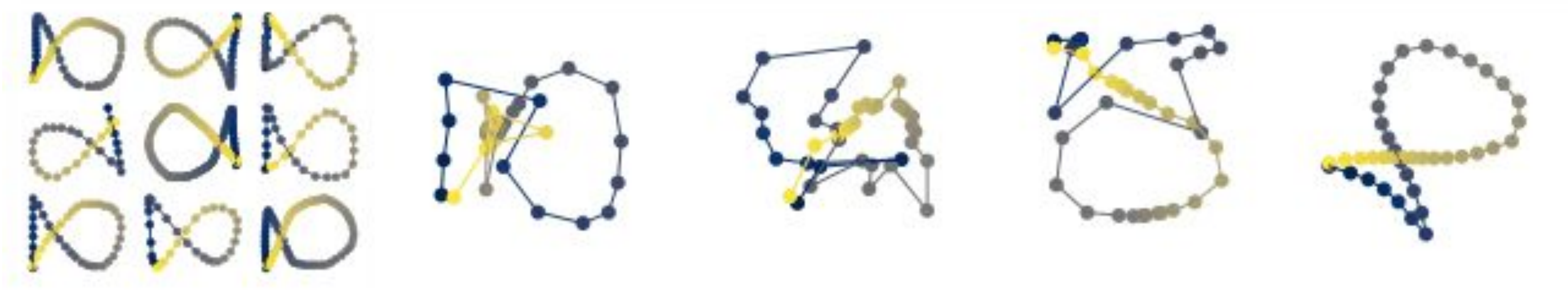
$$\mathrm{GDTW}(\boldsymbol{x},\boldsymbol{y}) = \min_{\mathbf{A}\in\mathcal{A}(T_x,T_y)} \sum_{ijkl} \mathcal{L}\Big[d_{\mathcal{X}}(x_i,x_k), d_{\mathcal{Y}}(y_j,y_l)\Big] A_{ij}A_{kl}$$



- Gromov Dynamic Time Warping: distance between time series living on potentially incomparable spaces
- Motivated by optimal transport theory

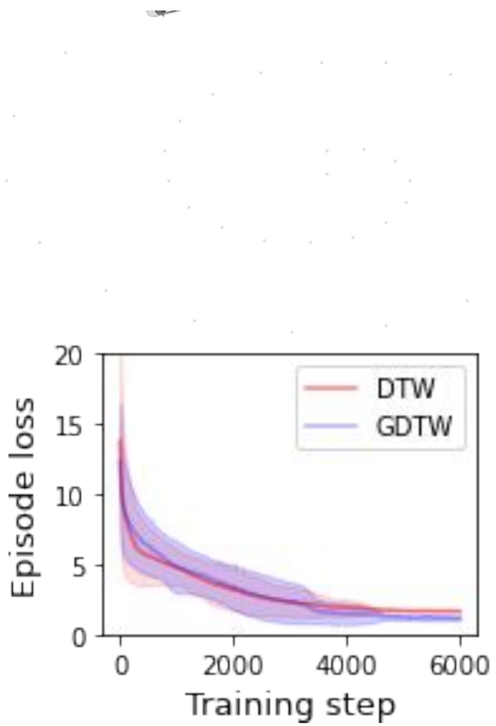
Barycentric Averaging

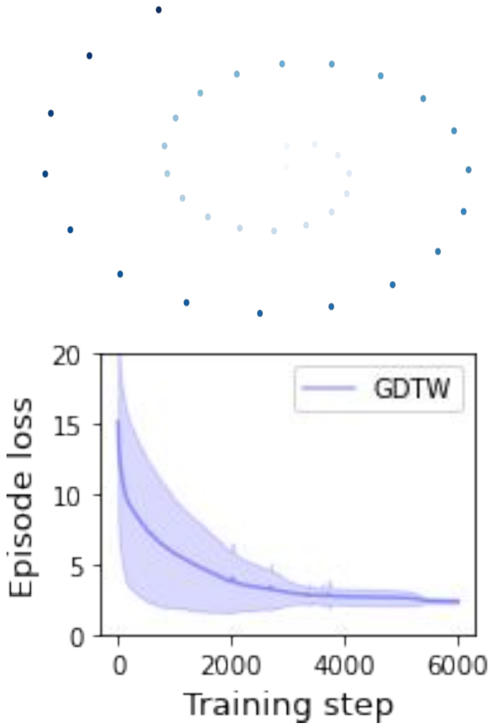
DTW | DTW-GI (rotations) | DTW-GI (rot., trans.) | GDTW



- GDTW allows averaging time series robustly thanks to invariances

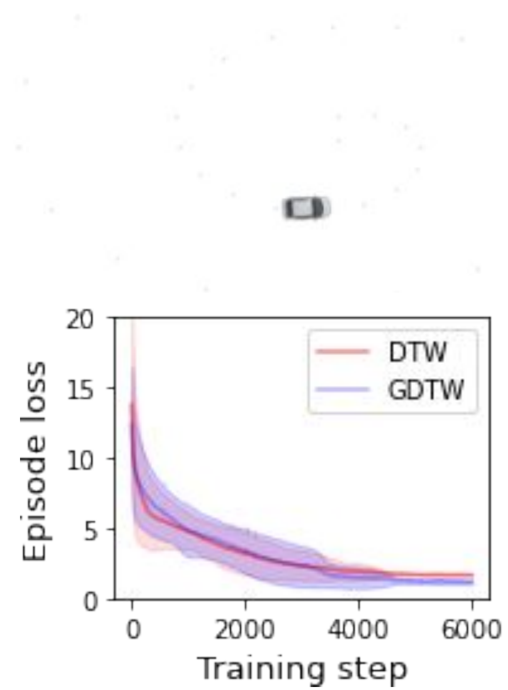
Imitation Learning

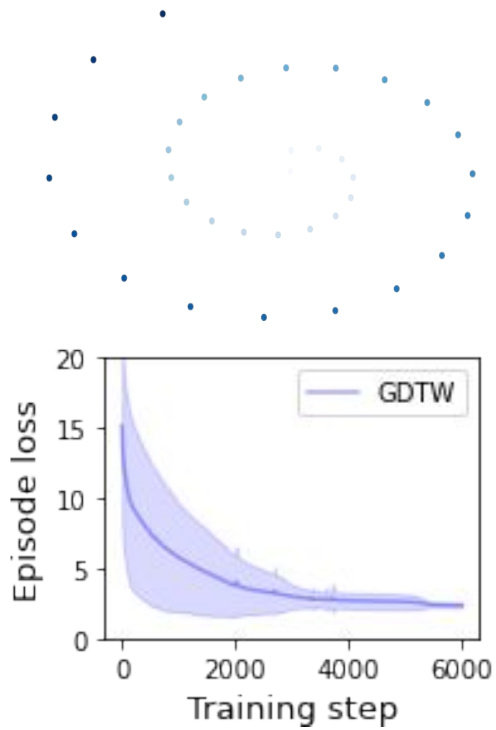




- Soft-GDTW: a soft version of GDTW allowing its use as differentiable loss
- Allows performing imitation learning when agent and expert are on different spaces

Imitation Learning





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- Allows performing imitation learning when agent and expert are on different spaces