Times Series Alignment on Incomparable Spaces

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Goal 1: Heterogeneous Alignments

- Goal: temporal alignments between time series from different modalities

Euclidean Points

Pixel Images
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

\[ \text{GDTW}(x, y) = \min_{A \in A(T_x, T_y)} \sum_{ijkl} \mathcal{L} \left[ d_X(x_i, x_k), d_Y(y_j, y_l) \right] A_{ij} A_{kl} \]

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

\[ d_X(x_i, x_k) \]

\[ d_Y(y_j, y_l) \]
Barycentric Averaging

- 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
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