

# A Wasserstein Subsequence Kernel for Time Series

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### **ETH Colors**

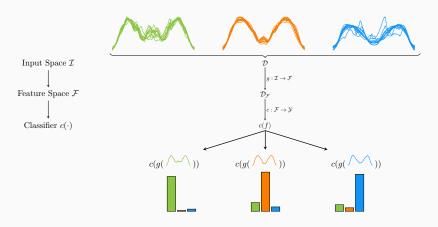


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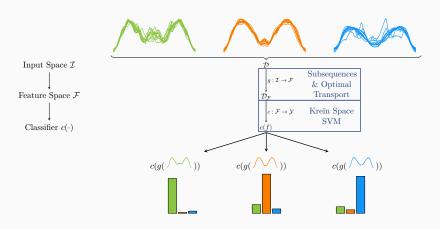
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## **Motivation**

### Time Series Classification in a Nutshell

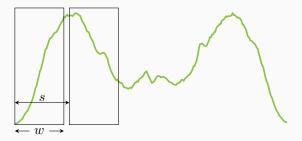


### Time Series Classification in a Nutshell



# Feature Space: Subsequences and Optimal Transport

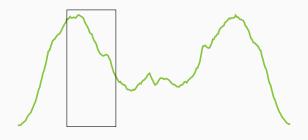
- Window Size w
- Stride s



- Window Size w
- Stride *s*

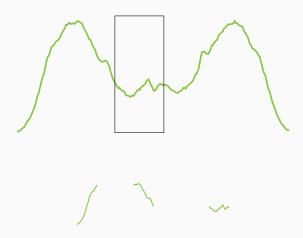


- Window Size w
- Stride s

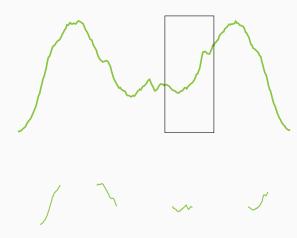




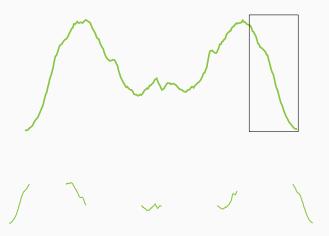
- Window Size w
- Stride s



- Window Size w
- Stride s



- Window Size w
- Stride s

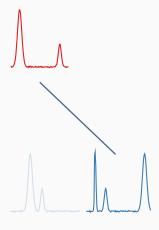


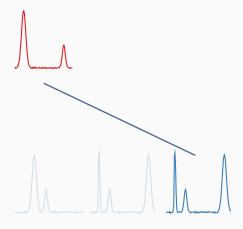
**Optimal Transport and the** 

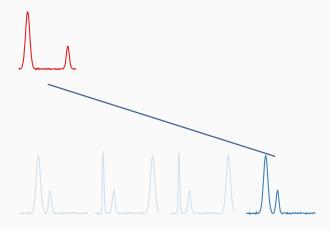
**Wasserstein Distance** 

## A Wasserstein Kernel for Time Series









### Definition (Wasserstein time series kernel)

Let  $T_i$  and  $T_j$  be two time series, and  $s_{i1},\ldots,s_{iU}$  as well as  $s_{j1},\ldots,s_{jV}$  be their respective subsequences. Moreover, let D be a  $U\times V$  matrix that contains the pairwise distances of all subsequences, such that  $D_{uv}:=\operatorname{dist}(s_{iu},s_{jv})$ , where  $\operatorname{dist}(\cdot,\cdot)$  denotes the usual Euclidean distance. The optimisation problem

$$W_{1}(T_{i}, T_{j}) := \min_{P \in \Gamma(T_{i}, T_{j})} \langle D, P \rangle_{F}, \qquad (1)$$

yields the optimal transport cost to transform  $T_i$  into  $T_j$  by means of their subsequences. Then, given  $\lambda \in_{>0}$ , we can define

$$WTK(T_i, T_j) := \exp(-\lambda W_1(T_i, T_j)), \qquad (2)$$

which we refer to as our Wasserstein-based subsequence kernel;

### Wasserstein Time Series Kernel

### **Algorithm 1** Wasserstein Time Series Kernel

```
Input: Time series for training and testing \mathcal{T}_{train}, \mathcal{T}_{test}; subsequence length w; kernel
       weight factor \lambda
Output: \mathcal{K}^{\text{train}}, \mathcal{K}^{\text{test}}
 1: S^{\text{train}} \leftarrow \text{SUBSEQUENCES}(\mathcal{T}_{\text{train}}, w) // Extract subsequences
 2: S^{\text{test}} \leftarrow \text{SUBSEQUENCES}(\mathcal{T}_{\text{test}}, w) // Extract subsequences
 3: for T_i \in \mathcal{T}_{train} do
 4:
        for T_i \in \mathcal{T}_{train} do
                \mathcal{D}_{ii}^{\mathsf{train}} \leftarrow \mathsf{W}_1\left(\mathcal{S}_i^{\mathsf{train}}, \mathcal{S}_i^{\mathsf{train}}\right)
                                                                     // Wasserstein distance calculation (train)
 6.
         end for
         for T_k \in \mathcal{T}_{\text{test}} do
 8.
               \mathcal{D}_{i\nu}^{\text{test}} \leftarrow W_1\left(\mathcal{S}_i^{\text{train}}, \mathcal{S}_{\nu}^{\text{test}}\right) // Wasserstein distance calculation (test)
 9:
            end for
10: end for
11: \mathcal{K}^{\mathsf{train}} \leftarrow \exp\left(-\lambda \mathcal{D}^{\mathsf{train}}\right) // Kernel matrix calculation
12: \mathcal{K}^{\text{test}} \leftarrow \exp(-\lambda \mathcal{D}^{\text{test}}) // Kernel matrix calculation
13: return \mathcal{K}^{train}, \mathcal{K}^{test}
```

### **Results**

### **Experiments**

Datasets UCR Time Series Archive

85 datasets

predetermined train/test splits

Hyperparameters Selected via a 5-fold cross-validation on the

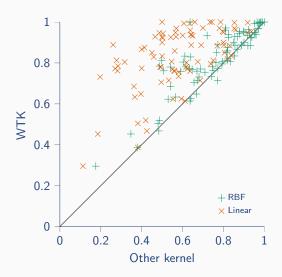
training set

**Evaluation metric** Classification accuracy

**Comparison partners** – Other kernels

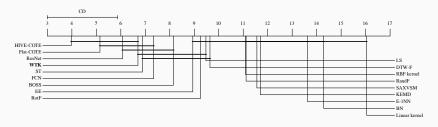
- DTW-1NN
- State-of-the-art methods

### **Comparison with Other Kernels**



### **Critical Difference Plot**

The classification performances of methods sharing horizontal bars are not significantly different.



# Take aways



### References i

### References