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Classification Methods for Temporal Data W. Grossmann

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- Example: Temperature monitoring of a container during transport
 - In case of "abnormal" temperature behavior the cargo is damaged and the transport has to be interrupted and returns to the origin
 - We distinguish three different scenarios as shown in the graphic



- General Problem formulation:
- Given are data of customer behavior represented as time sequences for process instances
- These data are classified into different groups
- Task: Find a classification rule which allows the assignment of a time sequence to one of the classes

- Strategies for solving this task:
 - Strategy 1: Define a similarity measure for the time sequences and apply nearest neighbor classification
 - Strategy 2: Extract from the time sequences features which allow the application of the classification methods for cross-sectional data
- In general, the first strategy is recommended if no additional knowledge about the time sequence is known

- Problem with the definition of similarity:
 - Time sequences may have different length
 - Similarity may be blurred by some temporal transformations like stretching or squeezing some parts of the time sequence (see example)
- We have to define the similarity by matching the observed values of two time sequences in such a way that the above defined effects are compensated

- Dynamic time warping allows the calculation of similarity
- Basic is the definition of a warping path:
 Given two sequences (x₁, x₂,..., x_N) and (y₁, y₂,..., y_M)
 Define a sequence (p₁, p₂,..., p_L) of matching indices pairs (i_l, j_l) such that

$$p_{1} = (1,1) \quad p_{L} = (N,M)$$

$$(i_{1} \leq i_{2} \leq \ldots \leq i_{L}) \text{ and } (j_{1} \leq j_{2} \leq \ldots \leq j_{L})$$

$$p_{\ell+1} - p_{\ell} \in \{(1,0), (0,1), (1,1)\}$$

The costs of a warping path is defined by

$$D_P = \sum_{\ell=1}^{L} d(i_{\ell}, j_{\ell}) = \sum_{\ell=1}^{L} |x_{i_{\ell}} - y_{j_{\ell}}|$$

- The dynamic time warping algorithm finds a warping path for two sequences with minimal costs
 - The word "dynamic" indicates that the algorithm is based on dynamic programming

- Application of the dynamic warping algorithm for all pairs of sequences defines a distance matrix for the observed time sequences
- We can apply now k-nearest neighbor classification for obtaining the classification rule
- Application for the example with 1-nearest neighbor is shown on CEWebS in *Klassifikation_NearestNeighbor*

Classification Based on Response Features

- In that case we extract from the time sequence a number of time independent characteristic features
- Examples of features:
 - Maximum and minimum of the time sequence
 - Temporal location of maximum and minimum
 - Breakpoints in the time sequence
 - Largest difference between two sequenced values
 - Length of the sequence
 - Area under the polygon defined by the sequence

Classification Based on Response Features

- More theoretically motivated features:
 - Transformation to frequencies and looking at the maximum frequency (Time sequence is sound or light)
 - Definition of a regression model for the time sequence
 - Definition of a representation language
- Based on these attributes one can apply methods of the classification of cross sectional data

Clustering of Time Sequences

- Clustering of time sequences can be done using the same principles as in the case of classification
- The definition of time warping defines a distance for the sequences which cam be used as input for cluster analysis (hierarchical or k-means)
- In the case of response features the distance between the time sequences is based on the response features