# **Dynamic time warping**

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Not to be confused with the Time Warp mechanism for discrete event simulation, or the Time Warp Operating System that used this mechanism.

In <u>time series analysis</u>, **dynamic time warping** (DTW) is an <u>algorithm</u> for measuring similarity between two temporal sequences which may vary in time or speed. For instance, similarities in walking patterns could be detected using DTW, even if one person was walking faster than the other, or if there were <u>accelerations</u> and decelerations during the course of an observation. DTW has been applied to temporal sequences of video, audio, and graphics data — indeed, any data which can be turned into a linear sequence can be analyzed with DTW. A well known application has been automatic <u>speech recognition</u>, to cope with different speaking speeds. Other applications include <u>speaker recognition</u> and online <u>signature recognition</u>. Also it is seen that it can be used in partial <u>shape matching</u> application.

In general, DTW is a method that calculates an <u>optimal match</u> between two given sequences (e.g. <u>time series</u>) with certain restrictions. The sequences are "warped" <u>non-linearly</u> in the time dimension to determine a measure of their similarity independent of certain non-linear variations in the time dimension. This <u>sequence</u> <u>alignment</u> method is often used in time series classification. Although DTW measures a distance-like quantity between two given sequences, it does't guarantee the <u>triangle inequality</u> to hold.

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# Implementation[edit]

This example illustrates the implementation of the dynamic time warping algorithm when the two sequences s and t are strings of discrete symbols. For two symbols x and y, d(x, y) is a distance between the symbols,

```
e.g. d(x, y) = |x - y|
int DTWDistance(s: array [1..n], t: array [1..m]) {
   DTW := array [0..n, 0..m]

   for i := 1 to n
        DTW[i, 0] := infinity
   for i := 1 to m
        DTW[0, i] := infinity
   DTW[0, 0] := 0

   for i := 1 to n
```

We sometimes want to add a locality constraint. That is, we require that if s[i] is matched with t[j], then |i - j| is no larger than w, a window parameter.

We can easily modify the above algorithm to add a locality constraint (differences marked in **bold italic**). However, the above given modification works only if |n - m| is no larger than w, i.e. the end point is within the window length from diagonal. In order to make the algorithm work, the window parameter w must be adapted so that  $|n - m| \le w$  (see the line marked with (\*) in the code).

## Fast computation[edit]

Computing the DTW requires O(N^2) in general. Fast techniques for computing DTW include SparseDTW<sup>[1]</sup> and the FastDTW.<sup>[2]</sup> A common task, retrieval of similar time series, can be accelerated by using lower bounds such as LB\_Keogh<sup>[3]</sup> or LB\_Improved.<sup>[4]</sup> In a survey, Wang et al. reported slightly better results with the LB\_Improved lower bound than the LB\_Keogh bound, and found that other techniques were inefficient.<sup>[5]</sup>

### Average sequence[edit]

Averaging for Dynamic Time Warping is the problem of finding an average sequence for a set of sequences. The average sequence is the sequence that minimizes the sum of the squares to the set of objects. NLAAF<sup>[6]</sup> is the exact method for two sequences. For more than two sequences, the problem is related to the one of the Multiple alignment and requires heuristics. DBA<sup>[7]</sup> is currently the reference method to average a set of sequences consistently with DTW. COMASA<sup>[8]</sup> efficiently randomizes the search for the average sequence, using DBA as a local optimization process.

# **Open Source software**[edit]

- The <u>lbimproved</u> C++ library implements Fast Nearest-Neighbor Retrieval algorithms under the GNU General Public License (GPL). It also provides a C++ implementation of Dynamic Time Warping as well as various lower bounds.
- The <u>FastDTW</u> library is a Java implementation of DTW and a FastDTW implementation that provides optimal or near-optimal alignments with an O(N) time and memory complexity, in contrast to the O(N^2) requirement for the standard DTW algorithm. FastDTW uses a multilevel approach that recursively projects a solution from a coarser resolution and refines the projected solution.
- The <u>R package dtw</u> implements most known variants of the DTW algorithm family, including a variety of recursion rules (also called step patterns), constraints, and substring matching.
- The mlpy Python library implements DTW.
- The <u>pydtw</u> C++/Python library implements the Manhattan and Euclidean flavoured DTW measures including the LB\_Keogh lower bounds.
- The JavaML machine learning library implements DTW.
- The ndtw C# library implements DTW with various options.
- <u>Sketch-a-Char</u> uses Greedy DTW (implemented in JavaScript) as part of LaTeX symbol classifier program.
- The MatchBox implements DTW to match Mel-Frequency Cepstral Coefficients of audio signals.
- Sequence averaging: a GPL Java implementation of DBA. [7]

# References[edit]

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## Further reading[edit]

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### See also[edit]

- Levenshtein distance
- Elastic matching

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