Introduction:

In several fields, the Dynamic Time Warping algorithm (DTW) is a well-known algorithm. Although it was first developed in the 1960s [1] and widely researched in the 1970s by using it for voice recognition [2], [3], it is today utilized in a variety of fields, including handwriting and online signature matching [4], [5], [6], and [7] identification of gestures and sign language. [6], time series clustering (time series databases search) [8], and data mining [9] [10] [11] [12] [13], computer animation and computer vision [14], security [15], chemical engineering and protein sequence alignment [16], music and signal processing [17] [14] [18].Through the application of the Dynamic Time Warping algorithm to the software development telemetry data, this work seeks to aid in the understanding of software metrics.

Pothole / shape detection information.

In this project we have also demonstrated the basic and actual working of DTW algorithm in one of the scripts. We have also considered one more use case of speech detection using DTW algorithm. For speech detection we use feature of KNN classifier for prediction, KNN classifier is trained with voice samples and it predict the sample which has been provided for testing, based the trained representation in the Distance matrix.

# METHODOLOGY:

1. DTW Algorithm:

As a time-series similarity measure that reduces the impacts of shifting and distortion in time by permitting "elastic" transformation of time series in order to find comparable shapes with varying phases, the DTW method has gained prominence. Given two time series, X = (x1, x2,...xN), N N and Y = (y1, y2,...yM), M N, represented by sequences of values (or curves represented by sequences of vertices), DTW offers the best solution in O(MN) time, however this could be done more quickly.

A graph of a line graph

Description automatically generated with medium confidence

Figure 1: Raw time series, arrows show the desirable points of alignment.

further by various methods including multi-scaling[17][19].The sole requirement for the data sequences is that they be sampled at evenly spaced intervals of time (this issue can be fixed by resampling). The local distance measure, which is defined to be a function, must be used to compare two separate sequences, X and Y, if they are taking values from the same feature space:

d : Φ × Φ → R ≥ 0

Value of d naturally has a low value when sequences are similar and a high one when they differ. Since the Dynamic Programming technique forms the basis of DTW, it is customary to refer to this distance function as the "cost function," with the goal of arranging all sequence points while minimizing the cost function (or distance).

The distance matrix C belongs to RNM representing all pairwise distances between X and Y is constructed at the beginning of the algorithm. The distance matrix in question is the local cost matrix for the alignment of two sequences X and Y :



A map of a topographical map

Description automatically generated

Figure 2: Time series alignment, cost matrix heatmap.

Once the local cost matrix built, the algorithm finds the alignment path

which runs through the low-cost areas - \valleys" on the cost matrix, Figure

2. This alignment path (or warping path, or warping function) defines

the correspondence of an element xi 2 X to yj 2 Y following the boundary

condition which assigns first and last elements of X and Y to each other,

Figure 3.

A graph of a function

Description automatically generated with medium confidence

Figure 3: The optimal warping path aligning time series from the Figure 1.

The alignment path built by DTW is a sequence of

points p = (p1; p2; :::; pK) with pl = (pi; pj) belongs to [1 : N] \* [1 : M] for l belongs to [1 : K]

which must satisfy to the following criteria:

1. Boundary condition: p1 = (1; 1) and pK = (N;M). The starting

and ending points of the warping path must be the \_rst and the last

points of aligned sequences.

2. Monotonicity condition: n1 <= n2 <= …… nK and m1 <= m2 <= …… mK.

This condition preserves the time-ordering of points.

3. Step size condition: this criterion limits the warping path from long

jumps (shifts in time) while aligning sequences. While this condition

will be discussed in greater details in the Section 3, for now will use the

basic step size condition formulated as



The cost function associated with a warping path computed with re-

spect to the local cost matrix (which represents all pairwise distances) will be:

A mathematical equation with numbers and symbols

Description automatically generated

The warping path which has a minimal cost associated with alignment

called the optimal warping path. We will call this path P\_.

By following the optimal warping path definition in order to find one, we

need to test every possible warping path between X and Y which could be

computationally challenging due to the exponential growth of the number of

optimal paths as the lengths of X and Y grow linearly. To overcome this

challenge, DTW employs the Dynamic Programming - based algorithm with

complexity only O(MN).

The Dynamic Programming part of DTW algorithm uses the DTW distance function

DTW(X; Y ) = cp\_(X; Y ) = min{cp(X; Y ); p belongs to PN\*M}.

where PN\*M is the set of all possible warping paths and builds the accumulated cost matrix or global cost matrix D which defined as follows:

A math equations on a white background

Description automatically generated

References

[1] R. Bellman and R. Kalaba, \On adaptive control processes,"

Automatic Control, IRE Transactions on, vol. 4, no. 2, pp. 1{9,

1959. [Online]. Available: http://ieeexplore.ieee.org/xpls/abs all.jsp?

arnumber=1104847

[2] C. Myers, L. Rabiner, and A. Rosenberg, \Performance tradeo\_s

in dynamic time warping algorithms for isolated word recognition,"

Acoustics, Speech, and Signal Processing [see also IEEE Transactions on

Signal Processing], IEEE Transactions on, vol. 28, no. 6, pp. 623{635,

1980. [Online]. Available: http://ieeexplore.ieee.org/xpls/abs all.jsp?

arnumber=1163491

[3] H. Sakoe and S. Chiba, \Dynamic programming algorithm optimization

for spoken word recognition," Acoustics, Speech and Signal Processing,

19

IEEE Transactions on, vol. 26, no. 1, pp. 43{49, 1978. [Online]. Avail-

able: http://ieeexplore.ieee.org/xpls/abs all.jsp?arnumber=1163055

[4] A. Efrat, Q. Fan, and S. Venkatasubramanian, \Curve matching, time

warping, and light \_elds: New algorithms for computing similarity

between curves," J. Math. Imaging Vis., vol. 27, no. 3, pp. 203{216, April

2007. [Online]. Available: http://dx.doi.org/10.1007/s10851-006-0647-0

[5] C. C. Tappert, C. Y. Suen, and T. Wakahara, \The state of the

art in online handwriting recognition," Pattern Analysis and Machine

Intelligence, IEEE Transactions on, vol. 12, no. 8, pp. 787{808, 1990.

[Online]. Available: http://dx.doi.org/10.1109/34.57669

[6] A. Kuzmanic and V. Zanchi, \Hand shape classi\_cation using dtw

and lcss as similarity measures for vision-based gesture recognition

system," in EUROCON, 2007. The International Conference on

"Computer as a Tool", 2007, pp. 264{269. [Online]. Available:

http://dx.doi.org/10.1109/EURCON.2007.4400350

[7] A. Corradini, \Dynamic time warping for o\_-line recognition of

a small gesture vocabulary," in RATFG-RTS '01: Proceedings of

the IEEE ICCV Workshop on Recognition, Analysis, and Tracking

of Faces and Gestures in Real-Time Systems (RATFG-RTS'01).

Washington, DC, USA: IEEE Computer Society, 2001. [Online].

Available: http://portal.acm.org/citation.cfm?id=882476.883586

[8] V. Niennattrakul and C. A. Ratanamahatana, \On clustering

multimedia time series data using k-means and dynamic time

warping," in Multimedia and Ubiquitous Engineering, 2007. MUE '07.

International Conference on, 2007, pp. 733{738. [Online]. Available:

http://dx.doi.org/10.1109/MUE.2007.165

20

[9] J. Gu and X. Jin, \A simple approximation for dynamic time warping

search in large time series database," 2006, pp. 841{848. [Online].

Available: http://dx.doi.org/10.1007/11875581 101

[10] C. Bahlmann and H. Burkhardt, \The writer independent online

handwriting recognition system frog on hand and cluster generative

statistical dynamic time warping," IEEE Trans. Pattern Anal. Mach.

Intell., vol. 26, no. 3, pp. 299{310, 2004. [Online]. Available:

http://dx.doi.org/10.1109/TPAMI.2004.1262308

[11] T. Kahveci and A. Singh, \Variable length queries for time series

data," in Data Engineering, 2001. Proceedings. 17th International

Conference on, 2001, pp. 273{282. [Online]. Available: http:

//dx.doi.org/10.1109/ICDE.2001.914838

[12] T. Kahveci, A. Singh, and A. Gurel, \Similarity searching for multi-

attribute sequences," in Scienti\_c and Statistical Database Management,

2002. Proceedings. 14th International Conference on, 2002, pp. 175{184.

[Online]. Available: http://dx.doi.org/10.1109/SSDM.2002.1029718

[13] W. Euachongprasit and C. Ratanamahatana, \E\_cient multimedia

time series data retrieval under uniform scaling and normalisation,"

2008, pp. 506{513. [Online]. Available: http://dx.doi.org/10.1007/

978-3-540-78646-7 49

[14] \Dtw-based motion comparison and retrieval," 2007, pp. 211{226.

[Online]. Available: http://dx.doi.org/10.1007/978-3-540-74048-3 10

[15] Z. Zhang, K. Huang, and T. Tan, \Comparison of similarity

measures for trajectory clustering in outdoor surveillance scenes,"

in ICPR '06: Proceedings of the 18th International Conference

on Pattern Recognition (ICPR'06). Washington, DC, USA: IEEE

Computer Society, 2006, pp. 1135{1138. [Online]. Available: http:

//dx.doi.org/10.1109/ICPR.2006.392

21

[16] J. Vial, H. Nocairi, P. Sassiat, S. Mallipatu, G. Cognon, D. Thiebaut,

B. Teillet, and D. Rutledge, \Combination of dynamic time warping

and multivariate analysis for the comparison of comprehensive

two-dimensional gas chromatograms application to plant extracts,"

Journal of Chromatography A, September 2008. [Online]. Available:

http://dx.doi.org/10.1016/j.chroma.2008.09.027

[17] M. Muller, H. Mattes, and F. Kurth, \An e\_cient multiscale approach

to audio synchronization," pp. 192{197, 2006.

[18] \Dynamic time warping," 2007, pp. 69{84. [Online]. Available:

http://dx.doi.org/10.1007/978-3-540-74048-3 4