## UCR Time Series Classification Archive

## Please reference as:

Dau, Hoang Anh, Eamonn Keogh, Kaveh Kamgar, Chin-Chia Michael Yeh, Yan Zhu, Shaghayegh Gharghabi, Chotirat Ann Ratanamahatana, Yanping Chen, Bing Hu, Nurjahan Begum, Anthony Bagnall, Abdullah Mueen and Gustavo Batista (2018). "The UCR Time Series Classification Archive." https://www.cs.ucr.edu/~eamonn/time_series_data_2018/

## Welcome!

Dear Colleague,

If you are reading this, you are interested in using the UCR Time Series Classification Archive. This archive is a superset of, and completely replaces [8]. The current version, thereafter, referred to as Fall 2018 expansion, will eventually replace Summer 2015 release [9]. The archive originally was born out of our frustration with papers reporting error rates on a single data set and claiming (or implicitly suggesting) that the results would generalize [6]. However, while we think the availability of previous versions of the UCR Archive has mitigated this problem to a great extent, it may have opened other problems.

1. Several researchers have published papers on showing "we win some, we lose some" on the UCR Archive. However, there are many trivial ways to get "win some, lose some" type results on these data sets (for example, just smoothing the data, or generalizing from 1-NN to $k$-NN etc.). Using the archive can therefore apparently add credence to poor ideas (very sophisticated tests are required to show small but true improvement effects [3][7]). In addition Gustavo Batista has pointed out that "win some, lose some" is worthless unless you know in advance which ones you will win on! [4]. Dau et al. discuss this in detail [10].
2. It could be argued that the goal of researchers should be to solve real-world problems, and that improving accuracy on the UCR Archive is at best a poor proxy for such real-world problems. Bing Hu has written a beautiful explanation as to why this is the case [2].
Despite the above, the community generally finds the archive to be a very useful tool, and to date, more than 1,200 people have downloaded the UCR archive, and it has been referenced several hundred times.
We are therefore delighted to share this resource with you. We encourage you to read the paper accompanies this new archive expansion [10]. The password you need to unlock the data download is available in this document, read on to find it.

Best of luck with your research.

Eamonn, Anh and the Team

## Data Format

Each of the data sets comes in two parts, a TRAIN partition and a TEST partition.
For example, for the Fungi data set we have two files, Fungi_TEST.tsv and Fungi_TRAIN.tsv The two files will be in the same format but are generally of different sizes.
The files are in the standard ASCII format that can be read directly by most tools/languages.
For example, to read the data of Fungi data set into MATLAB, we can type...

```
>> TRAIN = load('Fungi_TRAIN.tsv');
>> TEST = load('Fungi_TEST.tsv' );
```

...at the command line.

There is one time series exemplar per row. The first value in the row is the class label (an integer between 1 and the number of classes). The rest of the row are the data sample values. The order of time series exemplar carry no special meaning and is in most cases random. A small number of data sets have class label starting from 0 or -1 by legacy.


## Sanity Check

In order to make sure that you understand the data format, you should run this simple piece of code to test SyntheticControl data set (you can cut and paste it, it is standard MATLAB).

Note that this is slow "teaching" code. To consider all the data sets in the archive, you will probably want to do something more sophisticated (indexing, lower bounding etc).

Nevertheless, we highly recommend you start here.

TRAIN = load('SyntheticControl TRAIN.tSv'); \% Only these two lines need to be changed to test a different data set. TEST = load('Syntheticcontrol_TEST.tSv'); O Only these two lines need to be changed to test a different data set.


```
TRAIN_class_labels = TRAIN(:,1);
TRAIN(:,1) = [];
TEST_class_labels = TEST(:,1);
TEST(:,1) = [];
# = Pabels = TEST(:,1); % Pull out the class label
correct = 0; % Initialize the number Remove class labels from testing set.
for i = 1 : length(TEST_class_labels) % Loop over every instance in the test set
        classify_this_object = TEST(i,:);
    predicted_class = Classification_Algorithm(TRAIN,TRAIN_class_labels, classify_this_object);
    if predicted_class == this_objec\overline{ts_actual_class}
        correct = correct + 1;
    end;
    disp([int2str(i), ' out of ', int2str(length(TEST_class_labels)), ' done']) % Report progress
end;
```



```
disp(['The dataset you tested has ', int2str(length(unique(TRAIN_class_labels))), ' classes'])
disp(['The training set is of size ', int2str(size(TRAIN,1)),', and the test set is of size ',int2str(size(TEST,1)),'.'])
disp(['The time series are of length'', int2str(size(TRAIN,2))])
disp(['The error rate was ',num2str((length(TEST_class_labels)-correct )/length(TEST_class_labels))])
```



```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Here is a sample classification algorithm, it is the simple (yet very competitive) one-nearest
% neighbor using the Euclidean distance.
% If you are advocating a new distance measure you just need to change the line marked "Euclidean distance"
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function predicted_class = Classification_Algorithm(TRAIN,TRAIN_class_labels,unknown_object)
best_so far = inf;
    for i = 1 : length(TRAIN class labels)
        compare_to_this_objec
        distance
            if distance < best_so_far
                predicted_class = TRAIN_class_labels(i);
            best so far = distance;
        end
end;
```

```
299 out of 300 done
300 out of 300 done
The dataset you tested has 6 classes
The training set is of size 300, and the test set is of size 300.
The time series are of length 60
The error rate was 0.12
```

In this package we have produced a spreadsheet that gives basic information about the data sets (number of classes, size of train/test splits, length of time series etc)

In addition, we have computed the error rates for:

- Euclidean distance
- DTW, unconstrained
- DTW, after learning the best constraint in from the train set*
- Default rate (that is, the most probable class). To be consistent, we display default error rate, which is (1 - default_rate).
*Note that our simple method for learning the constraint is not necessary the best (as explained in the next slide).

You can download the entire spreadsheet displayed below in CSV format or Excel format.

| ID | Type | Name | Train | Test | Class | Length | ED (w=0) | DTW (learned_w) | DTW ( $\mathrm{w}=100$ ) | Default rate | Data donor/editor |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | Image | Adiac | 390 | 391 | 37 | 176 | 0.3890 | 0.3913 (3) | 0.3960 | 0.9591 | A. Jalba |
| 2 | Image | ArrowHead | 36 | 175 | 3 | 251 | 0.2000 | 0.2000 (0) | 0.2970 | 0.6971 | L. Ye \& E. Keogh |
| 3 | Spectro | Beef | 30 | 30 | 5 | 470 | 0.3330 | 0.3333 (0) | 0.3670 | 0.8000 | K. Kemsley \& A. Bagnall |
| 4 | Image | Beetlefly | 20 | 20 | 2 | 512 | 0.2500 | 0.3000 (7) | 0.3000 | 0.5000 | J. Hills \& A. Bagnall |
| 5 | Image | BirdChicken | 20 | 20 | 2 | 512 | 0.4500 | 0.3000 (6) | 0.2500 | 0.5000 | J. Hills \& A. Bagnall |
| 6 | Sensor | Car | 60 | 60 | 4 | 577 | 0.2670 | 0.2333 (1) | 0.2670 | 0.6833 | J. Gao |
| 7 | Simulated | CBF | 30 | 900 | 3 | 128 | 0.1478 | 0.0044 (11) | 0.0030 | 0.6644 | N. Saito |
| 8 | Sensor | ChlorineConcentration | 467 | 3840 | 3 | 166 | 0.3500 | 0.3500 (0) | 0.3520 | 0.4675 | L. Li \& C. Faloutsos |
| 9 | Sensor | CinCECGTorso | 40 | 1380 | 4 | 1639 | 0.1030 | 0.0696 (1) | 0.3490 | 0.7464 | physionet.org |
| 10 | Spectro | Coffee | 28 | 28 | 2 | 286 | 0.0000 | 0.0000 (0) | 0.0000 | 0.5357 | K, Kemsley \& A. Bagnall |
| 11 | Device | Computers | 250 | 250 | 2 | 720 | 0.4240 | 0.3800 (12) | 0.3000 | 0.5000 | J. Lines \& A. Bagnall |
| 12 | Motion | CricketX | 390 | 390 | 12 | 300 | 0.4230 | 0.2282 (10) | 0.2460 | 0.8974 | A. Mueen \& E. Keogh |
| 13 | Motion | CricketY | 390 | 390 | 12 | 300 | 0.4330 | 0.2410 (17) | 0.2560 | 0.9051 | A. Mueen \& E. Keogh |
| 14 | Motion | Cricketz | 390 | 390 | 12 | 300 | 0.4130 | 0.2538 (5) | 0.2460 | 0.8974 | A. Mueen \& E. Keogh |
| 15 | Image | DiatomSizeReduction | 16 | 306 | 4 | 345 | 0.0650 | 0.0654 (0) | 0.0330 | 0.6928 | ADIAC project |
| 16 | Image | Distal PhalanxOutlineAgeGroup | 400 | 139 | 3 | 80 | 0.3741 | 0.3741 (0) | 0.2302 | 0.5324 | L. Davis \& A. Bagnall |
| 17 | Image | DistalPhalanxOutlineCorrect | 600 | 276 | 2 | 80 | 0.2826 | 0.2754 (1) | 0.2826 | 0.4167 | L. Davis \& A. Bagnall |
| 18 | Image | Distal PhalanxTW | 400 | 139 | 6 | 80 | 0.3669 | 0.3669 (0) | 0.4101 | 0.7194 | L. Davis \& A. Bagnall |
| 19 | Sensor | Earthquakes | 322 | 139 | 2 | 512 | 0.2878 | 0.2734 (6) | 0.2806 | 0.7482 | A. Bagnall |
| 20 | ECG | ECG200 | 100 | 100 | 2 | 96 | 0.1200 | 0.1200 (0) | 0.2300 | 0.3600 | R. Olszewski |
| 21 | ECG | ECG5000 | 500 | 4500 | 5 | 140 | 0.0750 | 0.0749 (1) | 0.0760 | 0.4162 | Y. Chen \& E. Keogh |
| 22 | ECG | ECGFiveDays | 23 | 861 | 2 | 136 | 0.2030 | 0.2033 (0) | 0.2320 | 0.4971 | physionet.org, Y. Chen \& E. Keogh |
| 23 | Device | ElectricDevices | 8926 | 7711 | 7 | 96 | 0.4483 | 0.3806 (14) | 0.3990 | 0.7463 | A. Bagnall \& J. Lines |

## Worked Example

We can use the archive to answer the following question: Is DTW better than Euclidean distance for all/most/some/any problems?
As explained in [4], if DTW is only better on some data sets, this is not very useful unless we know ahead of time that it will be better. To test this we can build a Texas Sharpshooter plot (see [4] for details).
In brief, after computing the baseline (here, the Euclidean distance) we then compute the expected improvement we would get using DTW (at this stage, learning any parameters and settings), then compute the actual improvement obtained (using these now hardcoded parameters and settings).

When we create the Texas Sharpshooter plot , each data set fall into one of four possibilities.
In our worked example, we will try to optimize the performance of DTW, looking only at the training data and predict its improvement (which could be negative), in a very simple way.

Expected Improvement: We will search over different warping window constraints, from $0 \%$ to $100 \%$, in $1 \%$ increments, looking for the warping window size that gives the highest 1-NN training accuracy (if there are ties, we choose the smaller warping window size).

Actual Improvement: Using the warping window size we learned in the last phase, we test the holdout test data on the training set with 1-NN.

Note that there are better ways to do this (learn with increments smaller than $1 \%$, use $k$-NN instead of 1-NN, do cross validation within the test set etc). However, as the next slides show, the results are unambiguous even for this simple effort.

Texas Sharpshooter Plot [4]

| We expected to do worse, but we did better. | We expected an improvement and we got it! |
| :---: | :---: |
| We expected to do worse, and we did. | We expected to do better, but actually did worse. |

Expected Accuracy Gain

The results are strongly supportive of the claim that "DTW better than Euclidean distance for most problems."

We sometimes have difficultly in predicting when DTW would be better/worse, but many of the training sets are tiny, making such tests very difficult.

For example, 8 is BeetleFy, with just 20 train and 20 test instances. Here we expected to do a little better, but we did a little worse.

In contrast, for 66 (LargeKitchenAppliances) we had 375 train and 375 test instances and were able to more accurately predict a large improvement.

(after plotting in MATLAB, the code is in Appendix A, you can zoom in to avoid the visual clutter seen to the right).


## Suggested Best Practices/Hints

1. If you modify the data in anyway (add noise, add warping etc), please give the modified data back to the archive before you submit your paper (we will host it, and that way a diligent reviewer can test your claims while the paper is under review).
2. Where possible, we strongly advocate testing and publishing results on all data sets (to avoid cherry picking), unless of course you are making an explicit claim for only a certain type of data (i.e. classifying short time series). In the event you don't have space in your paper, we suggest you create an extended tech report online and point to it. Please see [4] (esp. Fig 14) for some ideas on how to visualize the accuracy results on many data sets.
3. If you have additional data sets, we ask that you donate them to the archive in our simple format.
4. When you write your paper, please make reproducibility your goal. In particular, explicitly state all parameters. A good guiding principle is to ask yourself: "Could a smart grad student get the exact same results as claimed in this paper with a day effort"?. If the answer is no, we believe that something is wrong. Help the imaginary grad student by rewriting your paper.
5. Where possible, make your code available (as we have done), it will make the reviewers task easier.
6. If you are advocating a new distance/similarity measure, we strongly recommend you test and report the 1-NN accuracy (as we have done). Note that this does not preclude the addition of other of tests (we strongly encourage additional test), however the 1-NN test has the advantage of having no parameters and allowing comparisons between methods.
7. Note that for 85 data sets of Summer 2015 release, the data are z-normalized by legacy. Paper [7] explains why this is very important. For 43 data sets of Fall 2018 expansion (this release), data are kept as is unless they were already z-normalized by donating source.

## Suggested Reading

1. Wang, Xiaoyue, et al. "Experimental comparison of representation methods and distance measures for time series data." Data Mining and Knowledge Discovery 26.2 (2013): 275-309.
2. Hu, Bing, Yanping Chen, and Eamonn Keogh. "Time series classification under more realistic assumptions." Proceedings of the 2013 SIAM International Conference on Data Mining. Society for Industrial and Applied Mathematics, 2013.
3. Hills, Jon, et al. "Classification of time series by shapelet transformation." Data Mining and Knowledge Discovery 28.4 (2014): 851-881.
4. Batista, Gustavo EAPA, Xiaoyue Wang, and Eamonn J. Keogh. "A complexity-invariant distance measure for time series." Proceedings of the 2011 SIAM international conference on data mining. Society for Industrial and Applied Mathematics, 2011.
5. Keogh, Eamonn, and Shruti Kasetty. "On the need for time series data mining benchmarks: a survey and empirical demonstration." Data Mining and knowledge discovery 7.4 (2003): 349-371.
6. Rakthanmanon, Thanawin, et al. "Addressing big data time series: Mining trillions of time series subsequences under dynamic time warping." ACM Transactions on Knowledge Discovery from Data (TKDD) 7.3 (2013): 10. If you are claiming that DTW is too slow... Maybe, but read this first.
7. Lines, Jason, Sarah Taylor, and Anthony Bagnall. "Time Series Classification with HIVE-COTE: The Hierarchical Vote Collective of Transformation-Based Ensembles." ACM Transactions on Knowledge Discovery from Data (TKDD) 12.5 (2018): 52.
8. Keogh, E., Zhu, Q., Hu, B., Hao. Y., Xi, X., Wei, L. \& Ratanamahatana, C. A. (2011). "The UCR Time Series Classification/Clustering Homepage".
9. Chen, Yanping, Eamonn Keogh, Bing Hu, Nurjahan Begum, Anthony Bagnall, Abdullah Mueen, and Gustavo Batista. 2015. "The UCR Time Series Classification Archive." https://www.cs.ucr.edu/~eamonn/time_series_data/
10. Dau, Hoang Anh, Anthony Bagnall, Kaveh Kamgar, Chin-Chia Michael Yeh, Yan Zhu, Shaghayegh Gharghabi, Chotirat Ann Ratanamahatana and Eamonn Keogh, "The UCR Time Series Archive." 2018 https://arxiv.org/abs/1810.07758 Early adopters (late 2018) please cite this, after early 2020, please check for a peer-reviewed version of this paper.
11. Bagnall, Anthony, et al. "The great time series classification bake off: a review and experimental evaluation of recent algorithmic advances." Data Mining and Knowledge Discovery31.3 (2017): 606-660.

## Appendix A:

 Texas Sharpshooter PlotsHere is the code we used to produce the Texas Sharpshooter plots.
function [] = plot_texas_sharpshooter(result_file)
Compute a Texas Sharpshooter plot of DTW over Euclidean Distance. See Batista, Wang and Keogh (2011) A Complexity-Invariant Distance Measure for Time Series. SDM 2011
\% Last updated April 2019 by Hoang Anh Dau
For example, if we want to construct the figure for comparison between Euclidean distance (ED) and Dynamic Time Warping distance (DTW), we compute the following statistics:
expected_accuracy_gain = DTW_train_accuracy / ED_train_accuracy \% actual_ac̄curacy_gain = DTW_tēst_accuracy / ED_test_accūacy
By definition, the train accuracy of DTW is always greater than the train \% accuracy of ED, which makes expected accuracy gain meaningless in this context. Therefore, we only use ED test accuracy, considering it as the normalizing factor

In the result spreadsheet texas plot 2018.csv:
\% row 1 is header
$\frac{5}{2}$ column 1 is datataset name
\% column 2 is ED train error rate
colum 4 s.
column 5 is DTW test error rate
\% Example of usage:
result file = 'texas plot 2018.csv'.
\% plot texas sharpshooter(result file).
$\%$
$\%$
$\%$
$\%$
read in result spreadsheet
result = importdata(result_file, ',', 1).
error_rates $=$ result.data;
convert error to accuracy, by subtracting from 1
texas_values = 1 - error_rates;
expected_accuracy_gain = texas_values(:,3)./texas_values (:, 2) ;
actual_accuracy_gain = texas_values(:,4)./texas_values(:,2);
igure;
scatter (expected_accuracy_gain,actual_accuracy_gain, 20, 'r', 'filled');
Xaxis = get(gca,'XLim');
Yaxis = get(gca,'YLim');
hold on; axis square;
\% bottom left quadrant
patch([Xaxis(1) 11 Xaxis(1)],[Yaxis(1) Yaxis(1) 1 1],[0.9843 0.84710 .5765$])$; top right quadrant
patch([1 Xaxis(2) Xaxis(2) 1],[1 1 Yaxis(2) Yaxis(2)],[0.9843 0.8471 0.5765]);
scatter (expected_accuracy_gain,actual_accuracy_gain, 20, 'r', 'filled');
xlabel('Expected Accuracy Gain');
ylabel('Actual Accuracy Gain');
plot with symbol as number
for $i=1$ : length(texas_values (:,1))
end
\% \% uncomment this to plot with symbol as data set name
\% note that the order of texas_names and texas_values must be the same
texas names $=$ result.textdata ( 2 :end, 1$)$;
for $i^{-}=1$. length (texas valus (
text (expected accuracy gain(i), actual accuracy gain(i), texas names(i,:),'rotation',+30)
\% end

Here the result summary file for making the Texas Sharpshooter plot.
texas_plot_2018.csv

- row 1 is header
- column 1 is data set name
- column 2 is ED train error rate
- column 3 is ED test error rate
- column 4 is DTW train error rate
- column 5 is DTW test error rate

Name, ED train, ED test, DTW train, DTW test
ACSF1,0.57,0.46,0.51,0.38
Adiac, $0.3949,0.3887,0.3897,0.3913$
AllGestureWiimoteX, $0.5033,0.4843,0.2833,0.2829$
AllGestureWi imoteY, $0.4433,0.4314,0.2267,0.27$
AllGestureWi imoteZ, $0.5967,0.5457,0.3667,0.3486$
ArrowHead, $0.0833,0.2,0.0833,0.2$
Beef, $0.5,0.3333,0.5,0.3333$
BeetleFly, 0.45,0.25,0.15,0.
BirdChicken, $0.3,0.45,0.15,0.3$
BME,0.1,0.1667,0,0.02
Car,0.3,0.2667,0.2833,0.2333
CBF, 0.1667,0.1478,0,0.0044
ChinaTown, 0.05,0.0466,0.05,0.0466
ChlorineConcentration, $0.3662,0.35,0.3662,0.35$
CinCECGTorso,0.15,0.1029,0.075,0.0645
Coffee, 0, 0,0,0
Computers, 0.444,0.424,0.248,0.38
CricketX,0.4026,0.4231,0.2,0.2282
CricketY,0.4564,0.4333,0.241,0.241
CricketZ,0.4231,0.4128,0.2256,0.2538
Crop,0.2928,0.2883,0.2928,0.2883
DiatomSizeReduction, $0.0625,0.0654,0.0625,0.0654$
DistalPhalanxOutlineAgeGroup, $0.1975,0.3741,0.1975,0.3741$ DistalPhalanxOutlineCorrect, 0.2167,0.2826,0.2117,0.2754 DistalPhalanxTW, 0.2475,0.3669, 0.2475, 0.3669 DodgerLoopDay, 0.5385,0.45,0.4744,0.4125 DodgerLoopGame, $0.25,0.1159,0.05,0.0725$ DodgerLoopWeekend, $0.05,0.0145,0,0.0217$ Earthquakes, $0.2578,0.2878,0.2329,0.273$ ECG200,0.14, 0.12,0.14,0.12 ECG5000,0.066,0.0751, 0.064,0.076 ECGFiveDays, $0.1739,0.2033,0.1739,0.2033$ lectricDevices,0.2911,0.4492,0.2911,0.4492
 OGVerticalsignal, $0.3398,0.558,0.2735,0.5249$ thanollevel,0.7044,0.726,0.6825,0.718 aceA1, $0.125,0.281,0.0375,0.1136$ acerucr, $0.345,0.2107,075,0.0878$ FiftyHords, $0.3644,0.3692,0,2289,0.241$ iftywords, $0.371,0.3692,0.2289,0.2418$ 1sh, $0.24,0.2171,0.2,0.1543$
FordB $0.3251,3938,0.3929,0.392$
FordB, 0.3251,0.3938,0.2929,0.3926
rese reezerSmallirain,0.1071,0.3242,0.1071,0.3242 ungi, 1774,1,0.1774
estureMidAirD1,0.4615,0.4231,0.3846,0.3615
estureMidAirD2, 0.524,0.5077,0.4375,0.4
GestureMidAirD3, 0.6635,0.6538,0.6394,0.6231 GesturePebbleZ1,0.1591,0.2674,0.0455,0.1744 GunPoint, $0.04,0.0867,0.04,0.0867$
GunPointAgeSpan, $0.0519,0.1013,0.0296,0.0348$ GunPointMaleVersusFemale, $0,0.0253,0,0.0253$ GunPointOldVersusYoung, $0.1029,0.0476,0.0221,0.0349$ Ham, $0.1468,0.4,0.1468,0.4$
Handoutlines, $0.143,0.1378,0.143,0.1378$ Haptics, $0.4839,0.6299,0.471,0.5877$ Herring, 0.5938,0.4844,0.4844,0.4688 ouseTwenty, $0.25,0.3361,0.05,0.0588$ nlineskate, 0.7,0.6582,0.58,0.6109 nsectepgregularTrain,0.2419,0.3213,0.1129,0.1727 Insectepgsmallirain, $0.4118,0.3373,0.3529,0.3052$ talyPowerDemand, $0.0448,0.0447,0.0448,0.0447$ LargeKitchenAppliances,0.384,0.5067,0.1733,0.2053 Lightning2, $0.2833,0.2459,0.1,0.1311$ Lightning $7,0.3571,0.4247,0.2,0.287$ Mallat, $0.0182,0.0857,0.0182,0.085$

## The Password

- As noted above. My one regret about creating the UCR Archive is that some researchers see improving accuracy on it as a sufficient task to warrant a publication. I am not convinced that this should be the case (unless the improvements are very significant, or the technique is so novel/interesting that it might be of independent interest).
- However, the archive is in a very contrived format. In many cases, taking a real-world data set, and putting it into this format, is a much harder problem than classification itself!
- Bing Hu explains this nicely in the introduction to her paper [2], I think it should be required reading for anyone working in this area.
- The password is the missing words from this sentence "Why would ****** use the archive and not acknowledge it?
- The sentence is in the Introduction of [10]. The paper is available for download on the UCR Archive webpage or at https://arxiv.org/abs/1810.07758


## Personal note from Eamonn

I am somewhat bemused by the hundreds of papers that use the UCR Archive, but do not acknowledge or thank the archivists.

Many such papers thank funding agencies, people that donated CPU time, friends that gave feedback etc. But many of these papers could not have been written without access to dozens of labeled time series data sets.

These dozens of labeled data sets were provided, completely for free! And these data sets represent (now) at least a thousand hours of work by my students and collaborators, to create or collect, to clean and annotate, to compute benchmarks etc.

It does seem like an acknowledgment would be classy ;-)

## Acknowledgments

The authors would like to thank Prof. Eamonn Keogh and all the people who have contributed to the UCR time series classification archive for their selfless work. We also thank the anonymous reviewers for their valuable advice.

This work has been supported by Major Project of High Resolution Earth Observation System of China (Grant No.03-Y20A04-9001-15/16), the CNES TOSCA-VEGIDAR Program, and CAS-CNRS Joint Doctoral Promotion Program.

## References

[1] Bailly, A., Malinowski, S., Tavenard, R., Guyet, T., Chapel, L., 2015. Bag-of-Temporal-SIFT-Words for time series classification. In: ECML/PKDD Workshop on Advanced Analytics and Learning on Temporal Data.
[2] Bartolini, I., Ciaccia, P., Patella, M., 2005. Warp: Accurate retrieval of shapes using phase of fourier descriptors and time warping distance. IEEE Transactions on Pattern Analysis and Machine Intelligence 27 (1), 142-147.
[3] Batista, G. E., Wang, X., Keogh, E. J., 2011. A complexity-invariant distance measure for time series. In: Proceedings of SIAM International Conference on Data Mining. Vol. 11. SIAM, pp. 699-710.
[4] Belongie, S., Malik, J., Puzicha, J., 2002. Shape matching and object recognition using shape contexts. IEEE Transactions on Pattern Analysis and Machine Intelligence 24 (4), 509-522.
[5] Bergmann, B., Hommel, G., 1988. Improvements of general multiple test procedures for redundant systems of hypotheses. In: Multiple Hypothesenprüfung/Multiple Hypotheses Testing. Springer, pp. 100-115.

## About the baseline results reported Before you ask

- Did you z-normalize the data before passing to the algorithm?
- There can be different implementations of DTW. Some implementations divide the distance by the warping path length; some use a different step patterns etc. We use MATLAB implementation of DTW [r1].

```
dist = dtw(time_series_1, time_series_2, window_size, 'squared');
```

- We use MATLAB implementation of $k$-NN [r2]

```
mdl = fitcknn(train_data, train_label, 'Standardize', 0, 'NSMethod', 'exhaustive');
```

- We use leave-one-out cross-validation to learn the warping constraint

```
cross_validation = crossval(mdl, 'LeaveOut', 'on');
```

- For constrained warping, if the percentage of time series length results in a real number, you can round up or round down. We round up.
- We round the error rate to four decimal places. For a more comprehensive result comparison and other resources, we recommend the UEA \& UCR Time Series Classification Repository [r3].


## About the baseline results reported How we handle special cases

- For time series of different lengths:
$>$ In storing data: We pad NaN (to the end) to the length of the longest time series. This makes it convenient when loading data into MATLAB.
$>$ In computing baselines: We add low amplitude random numbers (to the end) to the length of the longest time series to make all time series of equal length.

```
% pad_len is the length of the padding portion
time_series = [time_series, rand(1, pad_len)/1000];
```

- For time series with missing values
$>$ In storing data: Missing values are represented with NaN (if NaN is at the end of the time series, it is not real missing values).
$>$ In computing baselines: We use linear interpolation.
time_series = fillmissing(time_series, 'linear', 2, 'EndValues', 'nearest');
- There are 15 data sets fall into either of these special cases. No data sets is both of variable-length and with missing values. In the interest of reproducible research, we also provide the processed version (equal length, no missing values) of data that we used to produce the baseline results.

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## 43 data sets added in Fall 2018

The figures follow are intended to offer a quick inspection of the data. For readability, depending on the scenario, the data may be normalized or may be not, the number of exemplars per class may be one, three or many.

Class 0

## ACSF1

One exemplar per class, with z-normalization





Class 7



Class 9
2
0
0
-2
0

AllGestureWiimoteX
Three exemplars per class, without z-normalization

## Class 1




Class 5




Class 2






AllGestureWiimoteY
Three exemplars per class,
without z-normalization

Class 1
 Class 3


Class 5


Class 7



Class 2






AllGestureWiimoteZ
Three exemplars per class, without z-normalization


BME

Three exemplars per class, with z-normalization

Class 1


Class 2


Class 3


## Chinatown

Three exemplars per class, with z-normalization


Crop

Three exemplars per class, with znormalization

Class 1


Class 5


Class 9


Class 13


Class 17


Class 21


Class 2


Class 6


Class 10


Class 14


Class 18


Class 22



Class 7


Class 11


Class 15


Class 19


Class 23


Class 4



Class 12


Class 16




## DodgerLoopDay

One exemplar per class, with z-normalization


Class 3


Class 6


## DodgerLoopGame

One exemplar per class, without z-normalization

## Class 1




## DodgerLoopWeekend

One exemplar per class, without z-normalization

Class 1


Class 2


## EOGHorizontalSignal

Class 1





Three exemplars per class, with z-normalization


EOGVerticalSignal
Three exemplars per class, with z-normalization

Class 1


Class 4




Class 2


Class 5


Class 8






## EthanolLevel

Three exemplars per class, with z-normalization


## FreezerRegularTrain

Three exemplars per class, with z-normalization

Class 1


Class 2


## FreezerSmallTrain

One exemplar per class, with z-normalization

Class 1


Class 2


## Fungi

One exemplar per class, with z-normalization

Class 1



















GestureMidAirD1

Three exemplars per class, without z-normalization


GestureMidAirD2

Three exemplars per class, without z-normalization


GestureMidAirD3

Three exemplars per class, without z-normalization


## GesturePebbleZ1

Three exemplars per class, without z-normalization


## GesturePebbleZ2

Three exemplars per class, without z-normalization







## GunPointAgeSpan

Three exemplars per class, with z-normalization

Class 1


Class 2



Left) GunPoint recording of 2003, right) GunPoint recording of 2018. Top) Ann Ratanamahatana, bottom) Eamonn Keogh.
The female and male actors are the same individuals recorded fifteen years apart.

## GunPointMaleVersusFemale

Three exemplars per class, with z-normalization

Class 1


Class 2


## GunPointOldVersusYoung

Three exemplars per class, with z-normalization


## HouseTwenty

One exemplars per class, with z-normalization


## InsectEPGRegularTrain

Three exemplars per class, with z-normalization

## Class 1




Class 3


## InsectEPGSmallTrain

One exemplars per class, with z-normalization


## MelbournePedestrian

Three exemplars per class, with z-normalization

Class 1






Class 2






## MixedShapesRegularTrain

Three exemplars per class, with z-normalization

Class 1






## MixedShapesSmallTrain

One exemplar per class, with z-normalization

Class 1



Class 3




## PickupGestureWiimoteZ

Three exemplars per class, without z-normalization

Class 2







One exemplar per class, with z-normalization


PigArtPressure


One exemplar per class, with z-normalization
 without z-normalization

Class 0


Class 3


Class 6


Class 9


Class 1


Class 4


Class 7






## PowerCons

One exemplar per class, with z-normalization


## Rock

Three exemplars per class, with z-normalization


## SemgHandGenderCh2

One exemplar per class,
with z-normalization



## SemgHandMovementCh2

One exemplar per class, with z-normalization


## SemgHandSubjectCh2

One exemplar per class, with z-normalization

Class 1


Class 3


Class 5



Class 4


## ShakeGestureWiimoteZ

Three exemplars per class, without z-normalization


Class 5


Class 9


Class 2



Class 10



Class 7



Class 8


## SmoothSubspace

Thirty exemplars per class, with z-normalization



Class 3


## UMD

Three exemplars per class, with z-normalization


## 85 data sets from Summer 2015 release

The figures follow are intended to offer a quick inspection of the data. For readability, depending on the scenario, the data may be normalized or may be not, the number of exemplars per class may be one, three or many.

## Adiac

Three exemplars per class, with z-normalization




## ArrowHead

Three exemplars per class, with z-normalization


## Beef

Three exemplars per class, with z-normalization

Class 1






## BeetleFly

Three exemplars per class, with z-normalization

Class 1


Class 2


## BirdChicken

Three exemplars per class, with z-normalization

Class 1



## Car

Three exemplars per class, with z-normalization


CBF

Three exemplars per class, with z-normalization

Class 1


Class 2


Class 3


## ChlorineConcentration

Three exemplars per class, with z-normalization


## CinCECGTorso

Three exemplars per class, with z-normalization

Class 1





## Coffee

Three exemplars per class, with z-normalization


## Computers

One exemplar per class, with z-normalization

Class 1


Class 2


## CricketX

One exemplar per class, with z-normalization


## CricketY

One exemplar per class, with z-normalization

Class 1




Class 10


Class 2





Class 3


Class 6


Class 9



## CricketZ

One exemplar per class, with z-normalization


## DiatomSizeReduction

One exemplar per class, with z-normalization


## DistalPhalanxOutlineAgeGroup

Three exemplars per class, with z-normalization


## DistalPhalanxOutlineCorrect

Three exemplars per class, with z-normalization



## DistalPhalanxTW

Three exemplars per class, with z-normalization


## Earthquakes

One exemplar per class, with z-normalization


## ECG200

Three exemplars per class, with z-normalization


ECG5000

One exemplar per class, with z-normalization

Class 1


Class 2


Class 3


Class 4


Class 5


## ECGFiveDays

Three exemplars per class, with z-normalization



## ElectricDevices

One exemplar per class, with z-normalization


## FaceAll

One exemplar per class, with z-normalization


## FaceFour

Three exemplars per class, with z-normalization

## Class 1






## FacesUCR

One exemplar per class, with z-normalization

Class 1




Class 7


Class 9


Class 11



Class 2


Class 4



Class 8





## FiftyWords

One exemplar per class, with z-normalization











Fish

Three exemplars per class, with z-normalization



Class 6



## FordA

One exemplar per class, with z-normalization

## Class - 1



Class 1


## FordB

One exemplar per class, with z-normalization


## GunPoint

Three exemplars per class, with z-normalization

Class 1


Class 2


## Ham

Three exemplars per class, with z-normalization


## HandOutlines

Three exemplars per class, with z-normalization

Class 0


Class 1


## Haptics

Three exemplars per class, with z-normalization


## Herring

Three exemplars per class, with z-normalization

Class 1



## InlineSkate

Three exemplars per class, with z-normalization


## InsectWingbeatSound

One exemplar per class,
with z-normalization


## ItalyPowerDemand

Three exemplars per class, with z-normalization

Class 1


Class 2


## LargeKitchenAppliances

One exemplar per class, with z-normalization


## Lightning2

One exemplar per class, with z-normalization


## Lightning7

One exemplar per class, with z-normalization


## Mallat

One exemplar per class, with z-normalization

Class 2





## Meat

Twenty exemplars per class, with z-normalization

Class 1



Class 3


## Medicallmages

One exemplar per class, with z-normalization

Class 1


Class 3


Class 5


Class 7


Class 9


Class 2






## MiddlePhalanxOutlineAgeGroup

Three exemplars per class, with z-normalization




## MiddlePhalanxOutlineCorrect

Three exemplars per class, with z-normalization

Class 0


Class 1


## MiddlePhalanxTW

Three exemplars per class, with z-normalization


## MoteStrain

One exemplar per class, with z-normalization



## NonInvasiveFetalECGThorax1

One exemplar per class, with z-normalization























## NonInvasiveFetaIECGThorax2

One exemplar per class, with z-normalization


OliveOil

Three exemplars per class, with z-normalization

Class 1



Class 3


Class 4


OSULeaf

One exemplar per class, with z-normalization


## PhalangesOutlinesCorrect

Three exemplars per class, with z-normalization

Class 0



One exemplar per class,
with z-normalization


## Plane

Three exemplars per class, with z-normalization


## ProximalPhalanxOutlineAgeGroup

Three exemplars per class, with z-normalization

Class 1




## ProximalPhalanxOutlineCorrect

Three exemplars per class, with z-normalization


## ProximalPhalanxTW

Three exemplars per class, with z-normalization


## RefrigerationsDevices

One exemplar per class, with z-normalization

Class 1




## ScreenType

One exemplar per class, with z-normalization


## ShapeletSim

One exemplar per class,
with z-normalization


## ShapesAll

One exemplar per class, with z-normalization


## SmallKitchenAppliances

One exemplar per class, with z-normalization

Class 1




## SonyAIBORobotSurface1

Three exemplars per class, with z-normalization

Class 1


Class 2


## SonyAIBORobotSurface2

Three exemplars per class, with z-normalization


Class 2


## StarLightCurves

Three exemplars per class, with z-normalization

Class 1




## Strawberry

Three exemplars per class, with z-normalization

Class 1


Class 2


## SwedishLeaf

One exemplar per class, with z-normalization

Class 1


Class 4


Class 7




Class 2


Class 5


Class 8


Class 11



Class 3


Class 6



Class 12



## Symbols

Three exemplars per class, with z-normalization


## SyntheticControl

One exemplar per class, with z-normalization


## ToeSegmentation1

One exemplar per class, with z-normalization

Class 0


Class 1


## ToeSegmentation2

One exemplar per class, with z-normalization


## Trace

Three exemplars per class, with z-normalization

Class 1


Class 2


Class 3


Class 4


## TwoLeadECG

Three exemplars per class, with z-normalization


## TwoPatterns

One exemplar per class, with z-normalization

## Class 1





Class 4


## UWaveGestureLibraryAll

One exemplar per class, with z-normalization

Class 1


Class 3


Class 5


Class 7


Class 2


Class 4


Class 6



## UWaveGestureLibraryX

One exemplar per class, with z-normalization


Class 1




Class 2





## UWaveGestureLibraryY

One exemplar per class, with z-normalization


Class 2





## UWaveGestureLibraryZ

One exemplar per class, with z-normalization


## Wafer

One exemplar per class, with z-normalization


## Wine

Twenty exemplars per class, with z-normalization


## WordSynonyms

One exemplar per class, with z-normalization


## Worms

One exemplar per class, with z-normalization

Class 1



Class 3


Class 4


Class 5


## WormsTwoClass

One exemplar per class, with z-normalization


## Yoga

One exemplar per class, with z-normalization

Class 1


Class 2


