## Time Series Data Augmentation for Neural Networks by Time Warping with a Discriminative Teacher

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#### One Problem with Time Series Recognition and Deep Learning

Time series classification datasets are often small.

This is not ideal for modern deep learning methods.

Example: The UCR Time Series Archive contains 128 datasets. But, only 12 out of the 128 have more than 1,000 training patterns (and 1,000 is tiny).



#### **Time Series Data Augmentation**

In image recognition, data augmentation is normal and is used in most SotA methods.

- Examples
  - VGG random scaling, cropping, and color augmentation
  - AlexNet cropping, mirroring, and color augmentation
  - ResNet scaling, cropping, and color augmentation
  - **DenseNet** translation and mirroring
  - **Inception** cropping and mirroring

By comparison, outside of NLP, data augmentation in time series recognition isn't as widely used and there are no standard methods.



#### **Random Transformations**

Most of the commonly used **time series** data augmentations are adaptations borrowed from **image** recognition. Examples:





#### **Problem with Random Transformations**

The assumptions of each random transformation doesn't always hold for every time series domain.

Ex: Jittering (adding nose) doesn't always apply



UCR 50words In this dataset, all the patterns are smooth





Orange is original Blue is generated

Unipen 1b, the letter "O" Jittering doesn't make as much sense for pen-tip





#### **Other Time Series DA Methods**

One solution is to generate patterns from the distribution of features in the training set

Examples:

- GANs
- Domain specific generative models
- Pattern mixing
- Signal decomposition
- etc.



# Guided Warping For Time Series Data Augmentation



### **Dynamic Time Warping (DTW)**

Dynamic time warping (DTW) uses dynamic programming to match elements of time series. It is typically used as a global distance measure, but we use it for the dynamic alignment property.





### Guided Warping (Proposed)

In this work, we exploit the alignment property of DTW to align the elements of two time series.



Note: the patterns are only warped in the time domain.



### Guided Warping (Proposed)

Specifically, the elements of the input sample are warped to the time steps of the teacher sample using DTW.

In this way, the generated pattern has the features of the input sample at the time steps of the teacher sample.





### **Guided Warping (Proposed)**

In order to generate new samples, random samples from the same class are paired and then warped.

We can then use these new samples as augmented data.





#### **Problem: Guided Warping**

The problem is, just like many **pattern mixing** methods, the two intraclass samples are randomly selected.

There is no consideration to which patterns are mixed.





#### **Discriminative Guided Warping (Proposed 2)**

Thus, we propose taking a small subset of the training data and use a **nearest centroid classifier** based on DTW distance to determine the **most discriminative pattern**.

This pattern is used as the teacher pattern.





#### Results

#### Average of all 88 of the 2015 UCR TS Archive datasets

No Augmentation76.4457.24Jittering77.3258.35Rotation74.8454.78Scaling77.0657.98Magnitude Warping78.3058.04Time Warping78.1052.80Slicing79.1554.49Window Warping79.5857.49SPAWNER78.8458.98wDBA77.4256.01
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SPAWNER78.8458.98wDBA77.4256.01
wDBA 77.42 56.01
<b>RGW-D (Proposed)</b> 79.39 57.42
<b>RGW-sD (Proposed)</b> 79.27 56.43
<b>DGW-D (Proposed)</b> 80.12 56.01
<b>DGW-sD (Proposed)</b> 80.17 56.99



#### **Comparison to Other Pattern Mixing Methods**

**SPAWNER** 



wDBA ASD



Redundant patterns

DGW-sD (Proposed)



More useful patterns for DA





#### Summary

We proposed a new data augmentation method for time series called guided warping. Guided warping warps the elements of one time series to the time steps of another using DTW.

We demonstrated that the use of a discriminator can improve the performance of guided warping by selecting the most discriminate teacher.

We evaluated the proposed method on 88 UCR time series datasets using a CNN and an LSTM.

