Residual Attention Net for Superior Cross-Domain Time Sequence Modeling

Seth H. Huang  
AARC  
Huawei Technologies  
seth.huang@huawei.com

Xu Lingjie  
AARC  
Huawei Technologies  
xulingjie2@huawei.com

Jiang Congwei  
AARC  
Huawei Technologies  
jiangcongwei1@huawei.com

Abstract

We present a novel architecture, residual attention net (RAN), which merges a sequence architecture, universal transformer, and a computer vision architecture, residual net, with a high-way architecture for cross-domain sequence modeling. The architecture aims at addressing the long dependency issue often faced by recurrent-neural-net-based structures. This paper serves as a proof-of-concept for a new architecture, with RAN aiming at providing the model a higher level understanding of sequence patterns. To our best knowledge, we are the first to propose such an architecture. Out of the standard 85 UCR data sets, we have achieved 35 state-of-the-art results with 10 results matching current state-of-the-art results without further model fine-tuning. The results indicate that such architecture is promising in complex, long-sequence modeling and may have vast, cross-domain applications.

1 Introduction

Sequence modeling and time series modeling have been critical in real life applications. Their vast applications range from market demand forecast, missile defense, weather forecast, logistics calculation, shipping routes and cost prediction to even the spreading speed of contagions. However, there have been relatively few papers addressing sequence modeling in the artificial intelligence field, currently dominated by deep learning methodologies. There is also a surging interest in the investment field to incorporate deep learning methodologies to compete in ever-competitive financial markets [12]. However, there are three main challenges facing this type of data.

First, real life data may have long-dependency issues. The most popular sequence modeling methodology in artificial intelligence has been long-short-term memory (LSTM), which is a type of recurrent neural network. Second, financial data notoriously has high noise-to-signal ratio, which means the random information to actual pattern information can be quite imbalanced, and despite the modeling power of deep neural networks, the model learns primarily noises. It overfits easily and cannot generalize well [12].

Lastly, sequence data can often be non-stationary. This means that the patterns often change, and what the model learns may not be applicable to the new market scenarios. One way to compensate for this is to extend the look-back period to incorporate for historical data in the past so the model can recognize more pattern types [20]. This is also related to the first challenge as few models can
address the long-dependency issues - though LSTM was first created to tackle this challenge, it has not been able to solve this issue effectively and has since been replaced by other attention-based algorithms especially in the natural-language domain [15].

For sequence modeling tasks with deep learning, natural-language processing (NLP) has been at the forefront of innovations. For speech recognition and translation domains, many types of new architectures employing attention mechanism have been created such as attention-LSTM [13], transformer [7] (bert), and Bert [5].

[1] has shown that attention mechanism has been much more effective than LSTM in language tasks, and this idea was recently adopted by [18] to tackle sequence classification tasks. Compared to other modeling techniques, the authors claim attention-based methodologies are better at addressing long-dependency issues [3].

Additionally, some researchers have adopted techniques from the computer vision field and transfer the architectures to sequence modeling. For example, [2] uses convolution neural net for sequence modeling. [16]. Recently in the statistics field, [8] uses residual neural net (ResNet) for sequence modeling and outperforms many benchmarks based on statistical method. Some newly developed statistical methods such as Hive and Hive-Cote have shown to be extremely powerful in some sequence modeling [6], but they are ensemble methods based on numerous previous models, and they take extremely long time to train [17] and are not practical for real-life applications [17]. The limitations call for a sophisticated model architecture which can be readily applied in a practical setting while alleviating the above three challenges.

Typically, it is in theory inappropriate to use convolution-based methodology to tackle sequence modeling. Though it does not have long-dependency issues [14] as the data points are not passed through to the next block but are output directly in the pooling layer (average or global), convolution-based methodologies are "translation-invariant," which simply means time and sequence are not captured in CNN-based models - the architecture does not care where the pattern is and only cares that it appears in the sequence [21]. This is in theory inappropriate for time-driven sequence modeling especially for noisy data.

A recent series of papers [9, 10, 11] focusing on LSTM-FCN, which combines LSTM and fully convolutional net (check proper name) and achieved numerous state-of-the-art (SOTA) results on public benchmarks. This paper series will feature prominently in our paper and has inspired our work here.

LSTM-FCN architecture focuses on two branches, once based on LSTM (and a variant attention-LSTM, an LSTM with attention block), and the other based on a simple, three-block convolutions. For a recent analysis [9], in what they call an "ablation test," they present the data represented in the CNN filters. The intriguing part for us is that, based on the visual examination, the filters, depending on the data sets, sometimes have a smoothing effect and other times making the sequence noisier while retaining the overall sequence structure. Though not the focus of this paper, a hypothesis is that, while the sequence model is able to capture the time aspect of the data, the CNN architecture through the filters can make the models more resistant to noises.

Our work here elaborates on this concept and attempts to address the three main issues facing sequence modeling by combining a transformer architecture [19] and a residual, high-way architecture [22] and examine the effectiveness with UCR’s 85 public, sequence classification tasks.

2 Related Works

2.1 ResNet

Residual Networks called ResNet use residuals to reconstruct the mapping of the network. That is to say, the input $x$ is introduced again to the result, so that the weight of the stacked layer tends to zero.

$$ y = F(x, \{W_i\}) + x \quad (1) $$

Here $x$ and $y$ are the input and output vectors of the layers considered. The function $F(x, \{W_i\})$ is the residual mapping to be learned.
In order to match the dimension of $F(x, \{W_i\})$ and $x$, add a linear projection $W_s$ to the above equation as:

$$y = F(x, \{W_i\}) + W_s x$$  \hspace{1cm} (2)

### 2.2 Universal Transformer

The Universal Transformer, which is based on encoder-decoder architecture, has been proposed by [4]. The details of this architecture is briefly shown as follows.

**Encoder:** At first, for an input sequence with length $m$, initialize a matrix $H^0 \in \mathbb{R}^{m \times d}$, and each row of it is a $d$-dimensional embedding of the symbols at each position of the sequence. Then use the multi-headed dot-product self-attention mechanism to compute representations $H^t$ at step $t$, followed by a recurrent transition function. In addition, output and layer normalization are also added as the residual connections.

Use the scaled dot-product attention which combines queries $Q$, keys $K$ and values $V$ as follows

$$\text{ATTENTION}(Q, K, V) = \text{SOFTMAX}(\frac{QK^T}{\sqrt{d}})V$$  \hspace{1cm} (3)

$d$ is the number of columns of $Q$, $K$ and $V$. Then based on this equation, use the multi-head version with $k$ heads.

$$\text{MULTIHEADSELFATTENTION}(H^t) = \text{CONCAT}(\text{head}_1, \ldots, \text{head}_k)W^O$$  \hspace{1cm} (4)

where

$$\text{head}_1 = \text{ATTENTION}(H^tW^Q_i, H^tW^K_i, H^tW^V_i)$$  \hspace{1cm} (5)

and $W^Q, W^K, W^V, W^O \in \mathbb{R}^{d \times d/k}$.

So the revised representations $H^t \in \mathbb{R}^{m \times d}$ are computed as follows

$$H^t = \text{LAYERNORM}(A^t + \text{TRANSITION}(A^t))$$  \hspace{1cm} (6)

where

$$A^t = \text{LAYERNORM}((H^{t-1} + P^t) + \text{MULTIHEADSELFATTENTION}(H^{t-1} + P^t))$$  \hspace{1cm} (7)

$P^t \in \mathbb{R}^{m \times d}$ are fixed, constant, two-dimensional (position, time) coordinate embeddings, for the positions $1 \leq i \leq m$ and the time-step $1 \leq t \leq T$ separately for each vector-dimension $1 \leq j \leq d$,

$$P^t_{i,2j} = \sin i/10000^{2j/d} + \sin t/10000^{2j/d}$$  \hspace{1cm} (8)

$$P^t_{i,2j+1} = \cos i/10000^{2j/d} + \cos t/10000^{2j/d}. \hspace{1cm} (9)$$

Finally, the output of encoder is a matrix of $d$-dimensional vector representation $H^T \in \mathbb{R}^{m \times d}$ for the $m$ symbols of the input sequence after $T$ steps[4].

**Decoder:** The structure of the decoder is the same as the encoder. Specifically, after the self-attention function, the decoder also attends to the final encoder representation $H^T$ of each position in input sequence using the Equation(2). But the queries $Q$ obtained from projecting the decoder representation, and keys and values obtained from projecting the encoder representation[4]. During training, the decoder input is the target output, and finally, per-symbol target distributes are obtained:

$$P(y_{\text{pos}} | y_{[1: \text{pos}-1]}, H^T) = \text{SOFTMAX}(OH^T)$$  \hspace{1cm} (10)

where $O \in \mathbb{R}^d \times V$ is an affine transformation from the final decoder state to the output vocabulary size $V$. Softmax yields an $(m \times V)$-dimension output matrix normalized over its rows. Then select the maximal probability symbol as the next symbol.

Figure[4] is just the architecture of the combination of ResNet and Universal Transformer.
3 Experimental Results

Here, we present the experimental results between previously existing SOTAs, the LSTM-FCN results (in some cases exceeding the SOTAs) and the Resnet-Transformer results. For LSTM-FCN, we reproduced experimental results and took the best results among several training cycles, following the approach in [9]. Notice that, the reported results in [9] are fine-tuned for each data set, i.e. the model was adjusted to achieve the best results in individual datasets. The practicality of fine-tuning to boost the validation/out-of-sample data set performance may produce over-fitted models when not combined with ensemble methods. we tried to achieve similar effects by varying the size of fully-convolutional layers and then took the best results.

To compare, we provide the varied architectures by varying the depth size of the transformer branch and the ResNet feature maps.

Table 1: Performance comparison of proposed models with the rest

| dataset_name          | Existing SOTA | Best:Lstm-fcn | Vanilla: ResNet-Transformer | ResNet-Transformer |
|-----------------------|--------------|---------------|-----------------------------|-------------------|
|                       |              |               |                             | Transformer depth  |
|                       |              |               |                             | [128, 128, 64, 64] | [128, 128, 64, 64] | [64, 64, 128] |
| Adiac                 | 0.857        | 0.869565      | 0.84399                     | 0.849105          | 0.849105          | 0.849105       |
| ArrowHead             | 0.88         | 0.925714      | 0.891429                    | 0.891429          | 0.891429          | 0.897143       |
| ChlorineConcentration | 0.872        | 0.816146      | 0.849479                    | 0.863281          | 0.499375          | 0.816719       |
| InsectWingbeatSound   | 0.6525       | 0.666867      | 0.522222                    | 0.642424          | 0.535859          | 0.536364       |
| Lightning7            | 0.863        | 0.863014      | 0.821918                    | 0.849315          | 0.383562          | 0.835616       |
| Wine                  | 0.889        | 0.833333      | 0.851852                    | 0.87037           | 0.87037           | **0.907407**   |
| WordSynonyms          | 0.779        | 0.680251      | 0.661442                    | 0.65047           | 0.636364          | 0.678683       |
| Beef                  | 0.9          | 0.9           | 0.866667                    | 0.866667          | 0.866667          | 0.866667       |
| DistalPhalanxOutlineAgeGroup | 0.835       | 0.791367      | 0.81295                     | 0.776978          | 0.467626          | 0.776978       |
| DistalPhalanxOutlineCorrect | 0.82       | 0.797101      | **0.822464**                | **0.822464**      | **0.822464**      | **0.793478**   |
| DistalPhalanxTW       | 0.79         | 0.748201      | 0.733813                    | 0.748201          | 0.719424          | 0.741007       |
| ECG200                | 0.92         | 0.91          | 0.94                        | 0.95              | 0.94              | 0.93           |
| ECGFiveDays           | 1            | 0.987224      | 1                           | 1                 | 1                 | 1              |
| BeetleFly             | 0.95         | 1             | 1                           | 0.95              | 0.95              | 1              |
| BirdChicken           | 0.95         | 0.95          | 1                           | 0.9               | 1                 | 0.7            |
| ItalyPowerDemand      | 0.97         | 0.963071      | 0.965015                    | 0.969874          | 0.962099          | **0.971817**   |
| SonyAIBORobotSurface1 | 0.985        | 0.985025      | **0.988353**                | 0.978369          | 0.70819           | 0.985025       |
| SonyAIBORobotSurface2 | 0.962        | 0.972718      | 0.976915                    | 0.974816          | **0.98426**       | 0.976915       |
| MiddlePhalanxOutlineAgeGroup | 0.8144   | 0.668831      | 0.655844                    | 0.662338          | 0.623377          | 0.662338       |
| MiddlePhalanxOutlineCorrect | 0.8076   | 0.841924      | **0.848797**                | **0.848797**      | **0.848797**      | 0.835052       |
| MiddlePhalanxTW       | 0.612        | 0.603896      | 0.564935                    | 0.577922          | 0.551948          | 0.623377       |
| ProximalPhalanxOutlineAgeGroup | 0.8832  | 0.887805      | 0.888305                    | 0.892683          | 0.882927          | **0.892683**   |
| ProximalPhalanxOutlineCorrect | 0.918    | 0.931271      | **0.931271**                | **0.931271**      | 0.683849          | **0.924399**   |

continued on next page
| dataset_name                          | Existing SOTA | Best: lstm-fcn | Best: ResNet-Transformer | Transformer depth | ResNet feature maps |
|--------------------------------------|---------------|----------------|--------------------------|------------------|---------------------|
|                                      |               |                |                          |                  |                     |
| ProximalPhalanxTW                    | 0.815         | 0.843902      | 0.819512                 |                  |                     |
| MoteStrain                           | 0.95          | 0.938498      | 0.940895                 |                  |                     |
| MedicalImages                        | 0.792         | 0.796884      | 0.780263                 | 1                | [128, 128, 64, 64]  |
| Strawberry                            | 0.976         | 0.986486      | 0.986486                 | 1                | [128, 128, 64, 64]  |
| ToeSegmentation1                      | 0.9737        | 0.991228      | 0.969298                 | 4                | [128, 128, 64, 64]  |
| Coffee                               | 1             | 1              | 1                        | 4                |                     |
| CricketX                             | 0.821         | 0.792308      | 0.838462                 | 1                |                     |
| CricketY                             | 0.8256        | 0.802864      | 0.838462                 | 1                |                     |
| CricketZ                             | 0.8154        | 0.807692      | 0.820513                 | 1                |                     |
| UWaveGestureLibraryX                 | 0.8308        | 0.843663      | 0.780849                 | 1                |                     |
| UWaveGestureLibraryY                 | 0.7585        | 0.765215      | 0.664992                 | 1                |                     |
| UWaveGestureLibraryZ                 | 0.7725        | 0.795924      | 0.756002                 | 1                |                     |
| ToeSegmentation2                     | 0.9615        | 0.930769      | 0.976923                 | 1                |                     |
| DiatomSizeReduction                  | 0.967         | 0.970588      | 0.993464                 | 1                |                     |
| car                                  | 0.933         | 0.966667      | 0.95                     | 1                |                     |
| CBF                                  | 1             | 0.996667      | 1                        | 1                |                     |
| CinCECGtorso                          | 0.9949        | 0.904348      | 0.871739                 | 1                |                     |
| Computers                            | 0.848         | 0.852         | 0.86                     | 1                |                     |
| Earthquakes                          | 0.801         | 0.81295       | 0.755396                 | 1                |                     |
| ECG5000                              | 0.9482        | 0.948222      | 0.941556                 | 1                |                     |
| ElectricDevices                      | 0.7993        | 0.796665      | 0.774219                 | 1                |                     |
| FaceAll                              | 0.929         | 0.956213      | 0.881065                 | 1                |                     |
| FaceFour                             | 0.943182      | 0.954545      | 0.965909                 | 1                |                     |
| FacesUCR                             | 0.958         | 0.941463      | 0.957561                 | 1                |                     |
| Fish                                 | 0.989         | 0.971429      | 1                        | 1                |                     |
| FordA                                | 0.9727        | 0.976515      | 0.948485                 | 1                |                     |
| FordB                                | 0.9173        | 0.792393      | 0.838272                 | 1                |                     |
| GunPoint                             | 1             | 1              | 1                        | 1                |                     |
| Ham                                  | 0.781         | 0.809524      | 0.761905                 | 1                |                     |
| HandOutlines                         | 0.9487        | 0.950545      | 0.937838                 | 1                |                     |
| Haptics                              | 0.551         | 0.558442      | 0.564935                 | 1                |                     |
| Herring                              | 0.703         | 0.75          | 0.703125                 | 1                |                     |
| InlineSkate                          | 0.6127        | 0.489091      | 0.516364                 | 1                |                     |
| LargeKitchenAppliances               | 0.896         | 0.898667      | 0.8928                    | 1                |                     |
| Lighting2                            | 0.8853        | 0.819672      | 0.852459                 | 1                |                     |
| MALLAT                               | 0.98          | 0.98081       | 0.977399                 | 1                |                     |
| Meat                                 | 1             | 0.883333      | 1                        | 1                |                     |
| NonInvasiveFetalECGGThorax1          | 0.961         | 0.970483      | 0.953181                 | 1                |                     |
| NonInvasiveFetalECGGThorax2          | 0.955         | 0.961323      | 0.955216                 | 1                |                     |
| OliveOil                             | 0.9333        | 0.766667      | 0.966667                 | 1                |                     |
| OSULeaf                              | 0.988         | 0.893471      | 0.987603                 | 1                |                     |
| PhalangesOutlinesCorrect             | 0.83          | 0.83683       | 0.855478                 | 1                |                     |
| Phoneme                              | 0.3492        | 0.341772      | 0.363924                 | 1                |                     |
| plane                                | 1             | 1              | 1                        | 1                |                     |
| RefrigerationDevices                 | 0.5813        | 0.605333      | 0.605333                 | 1                |                     |
| ScreenType                           | 0.707         | 0.682667      | 0.693333                 | 1                |                     |
| ShapeletSim                          | 1             | 1              | 1                        | 1                |                     |
| ShapesAll                            | 0.9183        | 0.905         | 0.923333                 | 1                |                     |
| SmallKitchenAppliances               | 0.803         | 0.821333      | 0.808                    | 1                |                     |
| StarlightCurves                      | 0.9796        | 0.977295      | 0.978873                 | 1                |                     |
| SwedishLeaf                          | 0.9664        | 0.9792        | 0.9792                    | 1                |                     |
| Symbols                              | 0.9668        | 0.98794       | 0.9799                    | 1                |                     |
| SyntheticControl                     | 1             | 0.993333      | 1                        | 1                |                     |
| Trace                                | 1             | 1              | 1                        | 1                |                     |
| TwoPatterns                          | 1             | 0.99675       | 1                        | 1                |                     |
| TwoLeadECG                           | 1             | 1              | 1                        | 1                |                     |

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4 Conclusion

We present RAN as a potential new architecture for time-series or sequence-driven modeling. Out of the standard 85 UCR data sets, we have achieved 35 state-of-the-art results with 10 results matching current state-of-the-art results without further model fine-tuning. The results indicate that such
| Architecture          | model 1 | model 2 | model 3 | model 4 | model 5 | model 6 | model 7 | model 8 | model 9 | model 10 | model 11 |
|-----------------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| ResNet-fcn            | 0.0050  | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       |
| ResNet               | 0.0000  | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       |
| LSTM                 | 0.0000  | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       |
| LSTM-Fcn             | 0.0000  | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       |
| TSF                  | 0.0000  | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       |
| MLP                  | 0.0000  | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       |
| CNN                  | 0.0000  | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       |

Architecture is promising in complex, long-sequence modeling and may have vast, cross-domain applications.
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