Transformer Networks for Data Augmentation of Human Physical Activity Recognition

Sandeep Ramachandra
Ubiquitous Computing, University of Siegen
sandeep.ramachandra@student.uni-siegen.de

Alexander Hoelzemann
Ubiquitous Computing, University of Siegen
alexander.hoelzemann@uni-siegen.de

Kristof Van Laerhoven
Ubiquitous Computing, University of Siegen
kvl@eti.uni-siegen.de

ABSTRACT
Data augmentation is a widely used technique in classification to increase data used in training. It improves generalization and reduces amount of annotated human activity data needed for training which reduces labour and time needed with the dataset. Sensor time-series data, unlike images, cannot be augmented by computationally simple transformation algorithms. State of the art models like Recurrent Generative Adversarial Networks (RGAN) are used to generate realistic synthetic data. In this paper, transformer based generative adversarial networks which have global attention on data, are compared on PAMAP2 and Real World Human Activity Recognition data sets with RGAN. The newer approach provides improvements in time and savings in computational resources needed for data augmentation than previous approach.

CCS CONCEPTS
- Computing methodologies → Neural networks; Machine learning algorithms; • Human-centered computing → Ubiquitous computing.

KEYWORDS
Data Augmentation, Human Activity Recognition, Self Attention

1 INTRODUCTION
Deep learning networks have progressed substantially, both due to improvements in algorithms as well as availability of powerful computing hardware. These networks, however, require large amounts of data to train well, and such large benchmark datasets are not available for some domain, and human activity recognition from wearable sensors is such a field.

Data augmentation in the context of deep learning, is a technique used to increase the number of input data by adding modified data or by creating artificial data which are similar to real data [12]. Data augmentation acts as a regularizer, leading to generalized neural networks which give better results on unseen data. Image data can for instance be augmented by techniques such as geometric transformations or color space transformations which does not take much computational resources. Timeseries data like the raw output of inertial sensors is harder to augment, since any changes made to timeseries data due to augmentation cannot be visually identified. This is more complicated in human activity datasets since many activities like standing and sitting are very similar and any change may alter what activity the classifier identifies the data with. Annotation of collected data is a labour-intensive task and takes a long time for a sizable dataset [1]. The development of Generative Adversarial Networks (GAN) lead to neural networks outputting real-like data from random inputs. This is used to augment limited data. However, GANs do not always converge due to mode collapse arising from alternating gradient descent.

This work introduces a GAN architecture that is based on Transformer Networks. We evaluate our architecture with a recently published one [4] that is based on Long Short-Term Memory (LSTM). LSTMs has the disadvantage that they process incoming data sequentially. However, Transformers process data in a parallel stream which helps to speed up training drastically. These Transformer’s parameters grow quadratically with input size and can outstrip available GPU memory. However, for human activity that have small input sizes, this is not a big concern.

We validated our network with leave-one-subject-out (LOSO) cross-Validation and on two publicly available datasets, PAMAP2 [10] and Real World Human Activity Recognition (RWHAR) [13]. For the PAMAP2 dataset, we used 7 common activities with 27 sensor channels (3 dimensions each for accelerometer, gyroscope and magnetometer in 3 Inertial Measurement Units). For the RWHAR dataset, the dataset consists of 8 activities with 6 sensor channels (3 dimensions for accelerometer and gyroscope of the smartphone attached to the chest).

2 RELATED WORK
In sequence to sequence transformations like translating between two languages, transformers outperforms LSTM networks in both resources and in performance metrics [3], [14]. In Human activity recognition, Mahmud et al. [6] and Murahari et al. [7] uses transformers to capture the spatial temporal context from the feature space of sensor reading sequence and classify the sensor data. The transformer networks performs very well in this field as well. This suggests that the use of transformers in data augmentation can be beneficial.

Data augmentation is a topic under research in human activity recognition. Alawneh et al. [2] makes a case that using data augmentation in human activity recognition improves accuracy of trained classifiers. Li et al. [5] uses a convolutional GAN since Recurrent GANs do not converge consistently, to generate synthetic human activity physical data which were distinguishable by visualization techniques. Hoelzemann et al. [4] used a state of the art Recurrent GAN (RGAN), a GAN with an LSTM layer, for data augmentation with the resulting artificial data verified to be similar to original data.

Transformers in data augmentation has been explored in Zhang et al. [16] which utilises self attention from transformers to explore
long range dependencies in internal representation of images. Another network focusing on synthesizing images is the GANBERT or GAN with a bidirectional encoder representation from transformer [11] which uses self attention to generate difficult medical images like that from MRI and PET scans.

3 METHODOLOGY

Figure 1: Flowchart of the data augmentation process for human activity recognition.

(1) Ready the dataset for loading: This means that the dataset has been cleaned and loaded up in a format that is ready for the training and validation steps.
(2) Train the validation model: The main objective is to train a model of very high quality to classify signals to classes. The validation model chosen here is one DeepConvLSTM model [8] and one transformer model [15] for each of the datasets.
(3) Train the GAN models: In this work, an LSTM based Recurrent GAN and a transformer based GAN is compared. New models are trained for each class, so the dataset needs to be separated by the class.
(4) Validate artificial signal using validation model: The synthesized data from the generator needs to be validated using F1 score from the trained classifier.

3.1 GAN Models

The LSTM based Recurrent GAN (RGAN) (see figure 2) in both generators and in discriminators, has convolutions going into and coming out of the stacked LSTM layer [4]. The input to the generator is a 1D vector of random numbers sampled from a standard normal distribution. The input to the discriminator is a vector of shape cxL with c channels and L length (the PAMAP2 dataset has a shape of 27x100 and RWHAR has 6x50). The channels of the input are progressively increased using 1D convolutions (with padding) to increase the number of trainable parameters in the LSTM as well as increase the receptive field on original data. The stacked LSTM observes the trends in the data sequentially and its hidden state is used to classify the input data to N classes via a fully connected layer. There is a dropout before the fully connected layer providing regularization during training. The fully connected layer is realised by a 1D convolutional layer. The hyperparameters in this model are the noise length, generator LSTM layers, and discriminator’s LSTM’s hidden size and layers.

The Transformer GAN (TGAN) (see figure 3) follows a similar approach to the encoder of the traditional transformer encoder layer [14]. The inputs to both discriminator and generator are same as the ones for Recurrent GAN. The input is not processed sequentially as in Recurrent layers but in parallel. To give the network positional
awareness, a regular signal, typically sine/cosine signal, is added to the input. This is then passed to the multi head self attention blocks which is realised by a scaled dot product attention.

\[
\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right) V
\]  

The inputs Query(Q), Key(K), and Value(V) are obtained by a 1 to 1 1D convolution of input for each of the three. \(d_k\) is a scaling factor for the attention. The multi head attention block are followed by skip connections and then a layer normalization. Then a feedforward network in the shape of two fully connected layers going from input shape to a fixed dimension and then back to input shape. This is followed by another skip connection and layer normalization. This forms the encoder part of the network which is repeated sequentially so the network can learn the features of the input better. Finally, a fully connected layer realised by 1D convolutions with dropout is added so that the intermediary encoding done by the encoder is converted to the synthetic data in case of generator and to real/synthetic classification in case of discriminator. The hyperparameters available are the number of heads of the self attention layer of generator and discriminator, the number of encoder layers stacked in the generator and discriminator, the dimension of feedforward network, and the length of the noise vector.

4 RESULTS AND EVALUATION

![Figure 4: The confusion matrices in percentages for all trained models and both datasets. The overall validation F1 score of the models are (a) 96.21% (b) 91.8% (c) 97% (d) 92.6%. Table 1 shows the sizes of the trained validation models. The transformer classifiers are smaller, faster and have better validation F1 scores than DeepConvLSTM models.](image)

The models are trained with the given hyperparameters chosen by manual search through the configuration space [9]. Figure 4 shows the confusion matrices for the trained models. The Transformer outperforms the DeepConvLSTM in classification problems, both in time and in validation F1 scores (see figure 4. In each dataset, the transformer, despite being a smaller model consistently does better than the DeepConvLSTM model. In the classes where it is worse, it still performs very good. The margin of false classifications in those cases is only marginally lower.

The Transformer seems like a clear choice from figure 4 for use in the GAN as a validation model. However in actual use, this is not the case. RGAN appears to prefer DeepConvLSTM models and the Transformer GAN prefers a Transformer classifier models. They give higher validation F1 scores when paired with its preferred model and may not even train to completion with the other model. This may be due to the GAN learning the distribution which can pass the validation. The GANs seem to be able to learn the distribution needed when paired with a similar recurrent based layers i.e the LSTMs of the GAN can learn the distribution needed for DeepConvLSTM but not of the self attention layer and likewise for Transformer GAN. This is a curious observation of the behaviour of GAN, although it is not conclusively proven in this work. This is why there are 4 models trained for 4 data augmentation experiments.

Table 1 shows the performances of the 4 GANs which have been trained. The table lists the parameter size for the first try of the GAN training for generator and discriminator. The times and speeds shown are the average for the first activity only. The parameter sizes are truncated to first decimal place and are in thousands(K) and millions(M). "*" - The generated data for all activities in dataset did not satisfy the >95% validation model F1 score. The validation model training speed for transformer model was 4 to 4.5 times the speed of DeepConvLSTM model.

Table 1: Table of the performance of trained GAN models. RGAN stands for Recurrent GAN and TGAN stands for Transformer GAN. G is Generator, D is Discriminator, and V is Validation model. For speedup, the RGAN times are used as baseline for calculations for each dataset. The times and speeds shown are the average for the first activity only.

| Dataset  | Model  | Parameter Size | Augmented Data | Speed up (Time per epoch) |
|----------|--------|----------------|----------------|---------------------------|
| PAMAP2   | RGAN   | G : 17.6M      | Yes            | 1x (13 secs)             |
| RWHAR    | RGAN   | G : 2.10M      | No*            | 1x (24 secs)             |
| RWHAR    | TGAN   | G : 4.40M      | Yes            | 3x (8 secs)              |

Table 1 shows the performances of the 4 GANs which have been trained. The table lists the parameter size for the first try of the GAN training for generator and discriminator. The GAN models are so large as they were not optimized with a hyperparameter search.
Pearson correlation coefficient of the two variables is the Pearson correlation coefficient to make a simple comparison. The coefficient is a measure of the relationship between the two variables. The formula is

\[ r = \frac{N \sum xy - (\sum x)(\sum y)}{\sqrt{[N \sum x^2 - (\sum x)^2][N \sum y^2 - (\sum y)^2]}} \quad (2) \]

where \( r \) is the Pearson correlation coefficient of the two variables \( x \) and \( y \), and \( N \) is the number of pairs of scores in \( x \) and \( y \). The coefficient is scaled from -1 to 1 where 1 denotes that the two variables are proportional to each other and -1 denotes inverse proportionality. 0 means the two variables are not related to one another. Ideally, very closely related data like a real sample and perfect synthetics data should have a coefficient of 1.

Each axes of the data is compared to one another using the resulting coefficients are plotted for each activity. The figure 5 shows the graphs for the 4 dataset-model combinations. Any correlation of 0.8 and above correlates very well for use in data augmentation. This means that for PAMAP2, the Transformer GAN works splendidly with all activities of good quality, far better than Recurrent GAN in all activities. However there appears to be some issues with the RWHAR dataset for both models. Recurrent GAN fails in 3 activities and Transformer GAN in 4 activities. Activity 2 (climbing down) appears to be problematic since both have below 0.2 and transformer appears to be negatively correlated. This seems to be linked to one of the subjects of the dataset who wore their sensor upside down which has had a detrimental effect on both models but the transformer GAN is more severely afflicted. This suggests that the Transformer GAN is more sensitive to outlying data.

5 CONCLUSIONS AND OUTLOOK

This paper proposed a Transformer-based GAN for data augmentation of human activity data, in order to provide a speedup benefit over the existing Recurrent GAN and a performance benefit over a Convolutional GAN. This GAN is used along with a validation model which is used to verify that the output of the GAN is identifiable. The Transformer GAN is compared with Recurrent GAN using two public datasets, PAMAP2 and Real World Human Activity Recognition. In validation models, Transformer model outperformed DeepConvLSTM model in both F1 scores and in model parameter sizes. The Transformer GAN provides a 2 - 3 times speedup over Recurrent GAN in both datasets. The performance of the Transformer GAN is as good as if not better than the Recurrent GAN though it appears to be more sensitive to errant input data than Recurrent GAN. For that reason we are able to state that we (1) implemented the model and it generates data as needed for training (2) beat current benchmarks for data augmentation of human activity data with respect to the GAN training time (3) pointed out the importance to ensure that the produced data is variable but still belong to the original distribution of the input data and therefore recognizable by the classification network.

ACKNOWLEDGMENTS

We thank our anonymous reviewers for their many insightful suggestions and feedback.

REFERENCES

[1] Alireza Abedin, Farbod Motlagh, Qinfeng Shi, Hamid Rezaeioghi, and Damith Ranasinghe. 2020. Towards Deep Clustering of Human Activities from Wearables. In Proceedings of the 2020 International Symposium on Wearable Computers (Virtual Event, Mexico) (ISWC ’20). Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3410531.3414312

[2] Luay Alawneh, Tamam Alsarhan, Mohammad Al-Znati, Mahmoud Al-Ayyoub, Yaser Jararweh, and Hongtao Lu. 2021. Enhancing human activity recognition using deep learning and time series augmented data . 16 pages.

[3] Jonas Gehring, Michael Auli, David Grangier, Denis Yarats, and Yann N. Dauphin. 2017. Convolutional Sequence to Sequence Learning. http://arxiv.org/abs/1705.03122 arXiv: 1705.03122.

[4] Alexander Hoelzemann, Nimish Sorathiya, and Kristof Van Laerhoven. 2021. Data Augmentation Strategies for Human Activity Data Using Generative Adversarial
[5] Xi’ang Li, Jingi Luo, and Rabih Younes. 2020. ActivityGAN: Generative Adversarial Networks for Data Augmentation in Sensor-Based Human Activity Recognition. In Adjunct Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers (Virtual Event, Mexico) (UbiComp-ISWC ’20). Association for Computing Machinery, New York, NY, USA, 249–254. https://doi.org/10.1145/3410530.3414367

[6] Saif Mahmud, M Tanjid Hasan Tommoy, and Kishor Kumar Bhaumik. 2020. Human Activity Recognition from Wearable Sensor Data Using Self-Attention. 8 pages.

[7] Vishvak S. Murahari and Thomas Plötz. 2018. On Attention Models for Human Activity Recognition. In Proceedings of the 2018 ACM International Symposium on Wearable Computers (Singapore, Singapore) (ISWC ’18). Association for Computing Machinery, New York, NY, USA, 100–103. https://doi.org/10.1145/3267242.3267287

[8] Francisco Javier Ordoñez and Daniel Roggen. 2016. Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition. https://doi.org/10.1109/PERCOM.2016.7456521

[9] Sandeep Ramachandra. 2021. Implementation and Evaluation of Transformer Networks to augment sensor based Human Activity Data. https://github.com/sandeep-189/Data-Augmentation.git.

[10] Attila Reiss and Didier Stricker. 2012. Introducing a new benchmarked dataset for activity monitoring. 108–109 pages.

[11] Hoo-Chang Shin, Alvin Ihsani, Swetha Mandava, Sharath Turuvekere Sreenivas, Christopher Forster, Jiook Cha, and Alzheimer’s Disease Neuroimaging Initiative. 2020. GANBERT: Generative Adversarial Networks with Bidirectional Encoder Representations from Transformers for MRI to PET synthesis. http://arxiv.org/abs/2008.04393 arXiv: 2008.04393.

[12] Odongo Steven Eyobu and Dong Seog Han. 2018. Feature Representation and Data Augmentation for Human Activity Classification Based on Wearable IMU Sensor Data Using a Deep LSTM Neural Network. https://doi.org/10.3390/s18092892

[13] Timo Stützler and Heiner Stuckenschmidt. 2016. On-body localization of wearable devices: An investigation of position-aware activity recognition. 9 pages. https://doi.org/10.1109/PERCOM.2016.7456521

[14] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention Is All You Need. arXiv:1706.03762 [cs.CL]

[15] Neo Wu, Bradley Green, Xue Ben, and Shawn O’Banion. 2020. Deep Transformer Models for Time Series Forecasting: The Influenza Prevalence Case. http://arxiv.org/abs/2001.08317 arXiv: 2001.08317.

[16] Han Zhang, Ian Goodfellow, Dimitris Metaxas, and Augustus Odena. 2019. Self-Attention Generative Adversarial Networks. http://arxiv.org/abs/1805.08318 arXiv: 1805.08318.