Poster Abstract: Neural Sensor Translation

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ABSTRACT

Neural Machine Translation (*NMT*), a neural network based approach for language translation, has been shown to be more effective than traditional approaches like statistical machine translation. Inspired by *NMT*, we propose 'Neural Sensor Translation (*NST*)', a process of translating data sequences from one or a set of sensors to another using neural networks. *NST* is a data-driven approach for creating virtual sensors that have useful applications in sensor networks and internet of things. In this paper, we present a Bidirectional Long Short-Term Memory (BiLSTM) based neural network for sensor translation, and demonstrate the potential of the approach using sensor data from a home.

ACM Reference format:
Md Abu Sayeed Mondol, John A. Stankovic. 2016. Poster Abstract: Neural Sensor Translation. In *Proceedings of The ACM/IEEE Conference on Internet of Things Design and Implementation, Montreal, Canada, April 2019 (IoTDI 2019),* 2 pages.
DOI: 10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Neural Machine Translation (*NMT*) is a neural network based approach for translating a language to another by a computer. NMT has shown to be significantly more effective than traditional approaches like statistical machine translation. Inspired by *NMT*, we present 'Neural Sensor Translation (*NST*)', a process of translating data sequences from one or a set of sensors to another using neural networks. Like *NMT*, *NST* is a data-driven approach, but they are different in many other aspects including data type, data generation, performance metrics, and applications.

NST is our proposed new approach for creating virtual sensors that have many useful applications. They can be used to replace failed or malfunctioning sensors, to provide fine-grained sensing from sparsely deployed sensors, and to save energy of battery powered devices. One major problem of internet of things is the burden of maintenance, particularly in the long-run. The burden can be attenuated or delayed using more robust and durable equipment, but that increases cost for development and installation. Still, failure or malfunction of the equipment are inevitable. *NST* can be used to create a virtual sensor that emulates a failed or malfunctioning sensor as a measure to avoid repairing or replacing the device, or as a temporary solution to allow delayed maintenance.

IoTDI 2019, Montreal, Canada

DOI: 10.1145/nnnnnnn.nnnnnnn

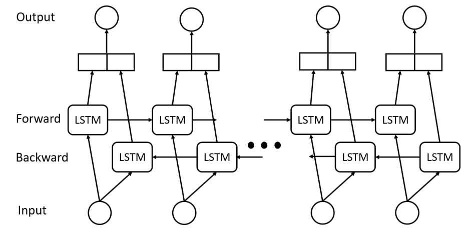

Figure 1: Architecture of the Bidirectional Long Sort-Term Memory (BiLSTM) method

Sensor translation can also be used for more localized sensing in a cost-effective way. For many smart systems like smart homes, buildings and cities, larger number of spatially distributed sensors enable more localized sensing that provides better utility and usually improves performance of the underlying algorithms. However, increased number of sensors result in significant cost for installation and maintenance. For example, few environment monitoring stations are available in many cities, and they can not provide very local information. We can use a mobile station to collect data of a location over a certain duration and create a virtual sensor for that location. The mobile station can be re-used for many locations. Sensor translation can also be used to save energy, particularly for battery powered devices where sensing requires significant energy.

In this paper, we present a Bidirectional Long Short-Term Memory (BiLSTM) based neural network for implementing sensor translation. We evaluated it using sensor data from a home. Results from this preliminary study demonstrate the potential of *NST*.

2 METHOD

Data from multiple sensors are often correlated, and the correlation is exploited to emulate a sensor. The correlation is better captured over sequences than by individual values. A Recurrent Neural Network (RNN) is effective in capturing patterns in sequences, and it is used widely for sequence-to-sequence modeling, particularly in natural language processing. We use a BiLSTM network for sensor translation, as shown in Figure 1. At each step, the outputs from the forward and the backward LSTM networks are concatenated and connected to a single node dense layer that predicts the corresponding value of the target sensor. We have used 16 nodes in each of the LSTM cells and the ReLU (Rectifier Linear Unit) activation function at the outputs.

3 EXPERIMENTS

We use data from temperature and relative humidity sensors deployed at a home [1]. There are two floors in the home, and temperature and humidity sensors are available on both of the floors. Here we use only the sensors from the first floor (Figure 2) where 4 nodes, each containing a temperature (T) and a relative humidity (RH)

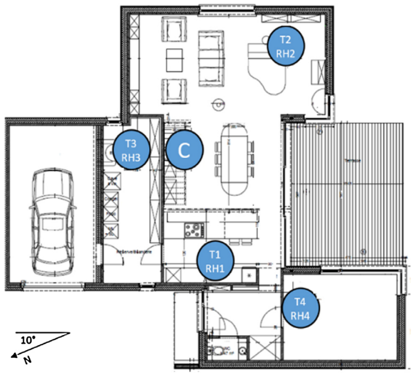

Figure 2: Temperature (T) and Relative Humidity (RH) sensors in the first floor of the home. This figure is from [1].

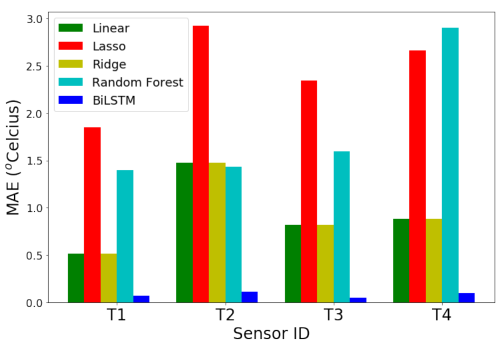

Figure 3: MAEs for emulating a temperature sensor from other temperature sensors.

sensor, are deployed at different places. Data have been collected for 137 days with 10-minute intervals. More details about the data are available in [1]. We use the first 80% data (about 110 days) for training and the remaining 20% (about 27 days) for testing. The data are segmented into sequences of length 24 that are used as input to the BiLSTM network.

The mean absolute errors (*MAE*) for emulating a sensor from the same type of other sensors (e.g., T1 from T2, T3, and T4) are shown in Figure 3 and Figure 4 for the temperature and the relative humidity sensors, respectively. Results for Linear, Lasso, Ridge, and Random Forest regression techniques are also shown. The errors of BiLSTM are very small compared to the other methods. The results demonstrate the effectiveness of *NST* in capturing the relationship between sensors.

The errors of BiLSTM for emulating a sensor from a single other sensor are listed in Table 1 and Table 2 for the temperature and the relative humidity sensors, respectively. We do not show the errors from the other methods due to space limitation, but they are significantly higher than BiLSTM as before. The errors from Figure 3 and Figure 4 for BiLSTM are also listed for comparison. We see that the error of translating one sensor to another is not significantly different than using three sensors. The result is context specific, and the error difference might be significant in other contexts.

Sensors can also be translated from one type to another. The last columns of Table 1 and Table 2 list the errors for translating a

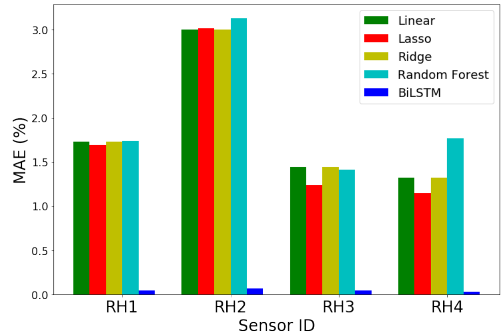

Figure 4: MAEs for emulating a relative humidity sensor from other relative humidity sensors.

Sensor	T1	T2	T3	T4	All Ts	Self RH
T1	0	0.09	0.09	0.1	0.07	0.18
T2	0.1	0	0.17	0.09	0.11	0.22
T3	0.05	0.14	0	0.1	0.05	0.20
T4	0.14	0.14	0.12	0	0.1	0.22

Table 1: MAEs for translating into a temperature sensor by the BiLSTM method.

Sensor	RH1	RH2	RH3	RH4	All RHs	Self T
RH11	0	0.05	0.05	0.04	0.05	0.09
RH2	0.07	0	0.08	0.08	0.07	0.12
RH3	0.04	0.04	0	0.02	0.04	0.06
Rh4	0.03	0.06	0.03	0	0.03	0.12

Table 2: MAEs for translating into a relative humidity sensor sensor by the BiLSTM method.

temperature sensor to a humidity sensor and a humidity sensor to a temperature sensor located in the same device. Though the errors are relatively higher than translating from similar sensors located in other nodes, they are not significantly high.

4 DISCUSSION

NST is a data-driven approach, and so translation error is context specific. Here, we presented results for temperature and humidity sensors in a home setting. The error rate might be significantly different for similar sensor translations in other settings like an industrial complex or an open area. The acceptable or usable error for sensor translation is not defined, rather they are application specific. *NST* does not require defining the relationship between the sensors explicitly, and so it can be used in many applications where the relationship is not well defined. However, *NST* would not work where the correlation between the sensors is not sufficient enough to achieve acceptable accuracy. Though we present results for relatively correlated sensors in a home setting, the results are encouraging, and show the potential of *NST*.

REFERENCES

[1] Luis M Candanedo, Véronique Feldheim, and Dominique Deramaix. 2017. Data driven prediction models of energy use of appliances in a low-energy house. *Energy and buildings* 140 (2017), 81–97.