SenseGen: A Deep Learning Architecture for Synthetic Sensor Data Generation

Project 6, Task 2 (Deep Learning for Multi-Layer Situational Understanding)

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***Abstract*—A large number of applications rely on personal sensory data from devices such as smartphones, and wearables. However, the prospect of sharing sensitive personal data often prohibits large-scale user adoption. To circumvent these issues and increase data sharing, synthetic data generation has been used as an alternative to real data sharing. The generated data should preserve only the required statistics of the real data (used by the apps to provide service) and nothing else and are used as a substitute for sensitive segments of real sensors data thus protecting privacy and resulting in improved analytics. In this paper, we take a step towards generating sensory data that are hard to distinguish from real sensory data, and make two contributions: first, we present a deep learning based architecture for synthesizing sensory data. This architecture comprises a *generator model*, using a stack of multiple Long-Short-Term-Memory networks and a Mixture Density Network; second, we use another LSTM network based *discriminator model* for distinguishing between the true and the synthesized data. Using a dataset of accelerometer traces, collected using smartphones of users doing their daily activities, we show that the deep learning based discriminator model can only distinguish between the real and synthesized traces with a maximum accuracy near to 50%.**

I. Introduction

A large number of applications rely on the collection of personal sensory data from devices such as smartphones, wearables, and home IoT devices. However, the prospect of sharing sensitive personal data, often prohibits large-scale user adoption and therefore the success of such systems. To circumvent these issues and increase data sharing, synthetic data generation has been used as an alternative to real data sharing. The generated data preserves only the required statistics of the real data (used by the apps to provide service) and nothing else and are used as a substitute for selective real data segments that are sensitive to the user thus protecting privacy and resulting in improved analytics.

In this paper, we present SenseGen – a deep learning based *generative model* for synthesizing sensory data. While deep learning methods are known to be capable of generating realistic data samples, training them was considered to be difficult requiring large amounts of data. However, recent work on generative models such as *Generative Adversarial Networks* [1] (GAN) has shown that it is possible to train these models with moderate sized datasets. GANs have proven successful in generating different types of data including photo-realistic high resolution images, and text and music composition.

Inspired by these models, we introduce SenseGen which is a deep learning-based approach for synthesizing sensors data. To summarize, we make two contributions. First, we present a deep learning architecture for synthesizing sensory data. This architecture comprises a *generator model*, which is a stack of multiple Long-Short-Term-Memory (LSTM) networks and a Mixture Density Network (MDN). Second, we use another LSTM network based *discriminator model* for distinguishing between the true and the synthesized data. Using a dataset of accelerometer traces, collected using smart-phones of users doing their daily activities, we show that the deep learning based discriminator model can only distinguish between the real and synthesized traces with a maximum accuracy near to 50%.

The rest of this paper is organized as follows: Section II provides a description for our model architecture and the training algorithm used. This is followed by Section III that describes our experimental design and initial results. Finally, Section IV concludes the paper.

II. Model Design

SenseGen consists of two deep learning models:

- Generator ($\mathcal{G}$): The generator $\mathcal{G}$ is capable of generating new synthetic time series data from random noise input.
- Discriminator ($\mathcal{D}$): The goal of the discriminator $\mathcal{D}$ is to assess the quality of the generator $\mathcal{G}$ outputs.

Both $\mathcal{G}$ and $\mathcal{D}$ are based on recurrent neural network models which have shown a lot of success in sequential data modeling. We describe the model details below.

Algorithm 1 Training algorithm

for $t = 1, 2, \ldots, T$ **do**
  Sample $\mathcal{X}_{true}$ minibatch from true data
  Sample $\mathcal{X}_{gen}$ minibatch from the generative model G
  Train the discriminative model $\mathcal{D}$ on the training set $(\mathcal{X}_{true}, \mathcal{X}_{gen})$ for 200 epochs
  Sample another $\mathcal{X}_{true}$ minibatch from true data
  Train the generative model $\mathcal{G}$ on the training set $(\mathcal{X}_{true})$ for 100 epochs
end for

A. Generative Model

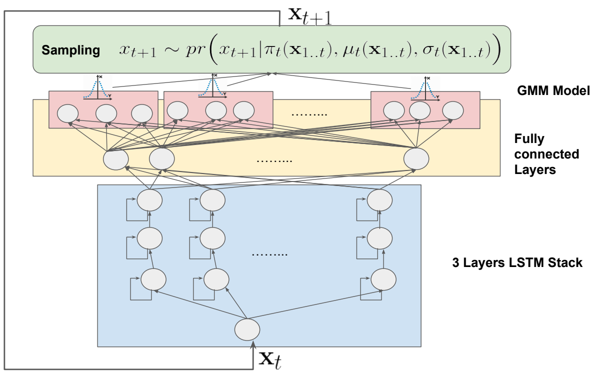

Fig. 1. Generative Model architecture

The generative model consists of a stack of 3 layers of LSTM units followed for a fully connected layer representing a mixture density network (MDN). This model is trained end-to-end by RMSProp and truncated back-propagation through time with a cost function chosen to increase the likelihood of the training data.

B. Discriminative Model

We built another model $\mathcal{D}$ whose goal is to distinguish between samples generated by $\mathcal{G}$. The discriminative model $\mathcal{D}$ is trained to distinguish between the samples coming from the dataset for real sensor traces $\mathcal{X}_{true}$ and others samples from the dataset $\mathcal{X}_{gen}$ which is generated by the model $\mathcal{G}$.

The output value this discriminative model when a given an input sensor values timeseries $\mathbf{x}_{test}$ is interpreted as the probability that the given input timeseries is coming from the real dataset $\mathcal{X}_{true}$. The training of the model $\mathcal{D}$ aims to minimize the cross-entropy loss $\mathcal{L}^{\mathcal{D}}$ with respect to the set of discriminitive model parameters.

$$\mathcal{L}^{\mathcal{D}}(\theta_{\mathcal{D}}) = -\left(\sum_{i=1}^{m} \log\left(\mathcal{D}(\mathcal{X}_{true}^{(i)})\right) + \log\left(1 - \mathcal{D}(\mathcal{X}_{gen}^{(i)})\right)\right)$$

III. Results and Analysis

For our experiments and evaluation studies, We use the Human Activity Recognition database [3] as our training data. The HAR database contains accelerometer and gyroscope recordings of 30 individuals while performing activities of daily living (ADL) (Walking, walking upstairs, walking downstairs, sitting, standing, and laying). Figure 2 shows a sample of both the real accelerometer sensor data and a sample of the generator model outputs.

A. Generating ECG signal

Patients physiological datasets are required for many research studies, However, they are hard to obtain for researchers due to privacy constraints. As another use case of our model, we studied the possibility of using hierarchical neural network model to generate synthetic Electrocardiography (ECG) signal.

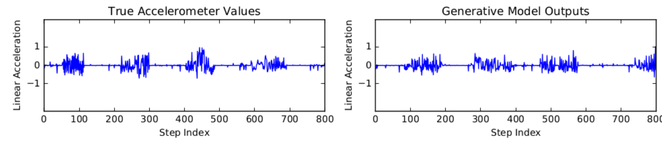

Fig. 2. Visual comparison between the real and generated accelerometer time-series samples

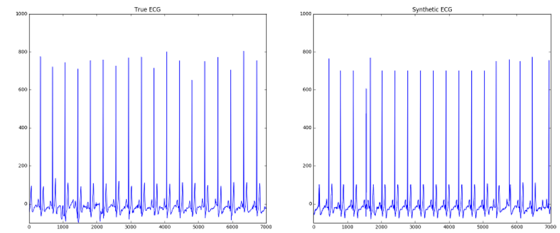

Fig. 3. Example of true ECG data (left) and model output synthetic ECG data (right)

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Figure III shows an example of both a true ECG signal from the training data (on the left) and an example of the model synethic ECG signal output (on the right).

IV. Conclusion

In this paper, we outlined our initial experiences of using a deep learning based architecture for synthesizing time series of sensory data. We identified that the synthesized data should be able to pass a deep learning based discriminator test designed to distinguish between the synthesized and true data. We then demonstrated that our generator can be successfully used to beat such a discriminator by restricting its accuracy to around 50%.

Acknowledgement

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