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Dual-memory neural networks for modeling cognitive activities of humans via wearable sensors

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ABSTRACT

Wearable devices, such as smart glasses and watches, allow for continuous recording of everyday life in a real world over an extended period of time or lifelong. This possibility helps better understand the cognitive behavior of humans in real life as well as build human-aware intelligent agents for practical purposes. However, modeling the human cognitive activity from wearable-sensor data stream is challenging because learning new information often results in loss of previously acquired information, causing a problem known as catastrophic forgetting. Here we propose a deep-learning neural network architecture that resolves the catastrophic forgetting problem. Based on the neurocognitive theory of the complementary learning systems of the neocortex and hippocampus, we introduce a dual memory architecture (DMA) that, on one hand, slowly acquires the structured knowledge representations and, on the other hand, rapidly learns the specifics of individual experiences. The DMA system learns continuously through incremental feature adaptation and weight transfer. We evaluate the performance on two real-life datasets, the CIFAR-10 image-stream dataset and the 46-day Lifelog dataset collected from Google Glass, showing that the proposed model outperforms other online learning methods.

1. Introduction

1.1. Wearable devices and the Lifelog dataset

Learning human behaviors in real-world settings is crucial for understanding human cognition in real life as well as for building human-aware intelligent systems such as personalized digital assistants. Recently, various types of wearable devices, including smart watches and Google Glass, have become popular. These devices can see and hear what the device user sees and hears; which differentiates them from classical agents such as personal computers or smartphones. To simulate the real-world environment, we collected a Lifelog dataset using Google Glass from three participants over 46 days. This dataset has two properties. First, high-level context is hidden in the raw data stream; e.g., an egocentric video recorded during a meeting includes various types of high-level contexts, although the data is only a stream of pixels and audio signals. Second, the data streams are often non-stationary; e.g., the life patterns of a student during the holiday and school term are different. We are interested in continually adapting the context-aware activity recognizer rapidly from human behavior gathered through wearable devices. Two algorithmic techniques are required to manage this task. First, a deep learning method is necessary to manage raw data efficiently. Second, an online learning algorithm is required to keep track of fast-changing life patterns of user behavior.

1.2. Online learning of deep neural networks and catastrophic forgetting

Online learning of deep neural networks (DNNs) that cover a lifetime is challenging, but learning over long time periods is fundamental to developing a real-time personalized recognizer. Assume that you trained a neural network using a first training, which was user data from the first week. Subsequently, a second

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0893-6080/

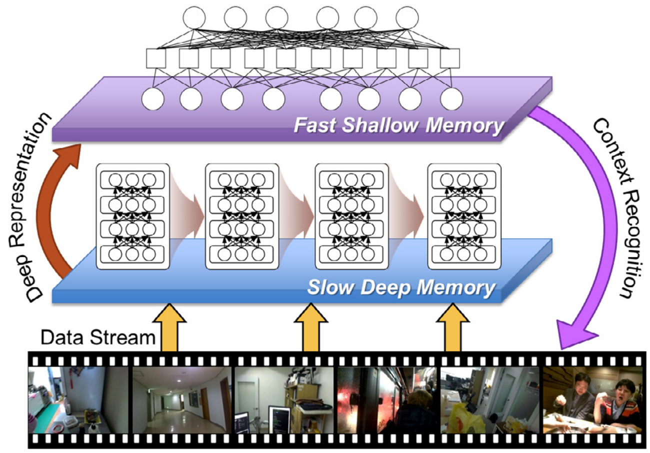

Fig. 1. Learning framework proposed in this work.

training dataset becomes available and is user data from the second week. You can train the neural network with the second training dataset; however, the information from the first training dataset may be lost, especially when the data stream is non-stationary. In short, when new data becomes available, the neural network often forgets old data; this phenomenon is known as catastrophic forgetting (Goodfellow, Mirza, Xiao, Courville, & Bengio, 2013).

Various approaches have been proposed for online learning of DNNs. Recently, online fine-tuning of convolutional neural networks (CNNs) using a simple online stochastic gradient descent (SGD) was successful at inferring a visual tracking task (Nam & Han, 2016). However, this ad hoc method does not guarantee the retention of old data. Several studies have adopted an incremental ensemble learning approach, whereby a weak learner is made to use the online dataset, and these multiple weak learners are combined to obtain a better predictive performance (Polikar, Upda, Upda, & Honavar, 2001). Unfortunately, in our experiment, a simple voting method with weak learners trained from a relatively small online dataset was unsuccessful; we presumed that a relatively small online dataset is insufficient for learning highly expressive representations of DNNs.

1.3. Complementary learning systems theory

To solve the problem of catastrophic forgetting, we apply the concept of complementary learning systems (CLS) theory; a framework based on the idea of a dual learning system structure in the brain (McClelland, McNaughton, & O'Reilly, 1995; O'Reilly, Bhattacharyya, Howard, & Ketz, 2014). According to the CLS theory, there are two critical areas in the brain that affect online learning: the neocortex and the hippocampus, with complementary functions. From the machine learning perspective, the neocortex is analogous to a deep neural module that can gradually learn to extract structure from real-world sensor streams (Guyonneau, VanRullen, & Thorpe, 2004). Further, corroborative evidence from cognitive neuroscience shows that the behavior of performance-optimized deep CNNs closely match the neural responses in the higher visual cortex of the brain in monkeys (Yamins et al., 2014). However, the key limitations introduced by the idea of online learning are that the neocortex does not rapidly learn a new concept in a single attempt nor does it process data at the instance-level to weigh specific events appropriately. In contrast, the hippocampus alleviates this problem by allowing rapid and individuated storage to memorize a new instances (Knierim & Neunuebel, 2016; Treves & Rolls, 1992). There is evidence that the hippocampus allows general statistics of the environment to be circumvented by weighting procedures such that statistically unusual but significant events may be afforded a privileged status (Bendor & Wilson, 2012; Carr, Jadhav, & Frank, 2011). However, a hippocampal system alone would be insufficient for continuous learning because of limitations on memory capacity and generalization ability.

1.4. Dual memory architecture

To address the issues of a neocortex-like or hippocampal-like system alone, we propose a dual memory architecture (DMA) (Fig. 1). The DMA trains two memory structures: one is an ensemble of DNNs, and the other consists of a shallow network that uses hidden representations of the DNNs as input. These two memory structures are designed to use different strategies. The ensemble of DNNs learns new information to adapt its representation to new data, whereas the shallow network aims to manage non-stationary distribution and unseen classes more rapidly.

Some additional techniques for online deep learning are incorporated in this study. First, the transfer learning method via weight transfer is applied to maximize the representation power of each neural module in online deep learning (Yosinski, Clune, Bengio, & Lipson, 2014). Second, the multiplicative Gaussian hypernetwork (mGHN) and its online learning method are developed. An mGHN concurrently adapts both structure and parameters to the data stream using an evolutionary method and a closed-form-based sequential update, which minimizes loss of past data. The mGHN possesses two good properties for online learning: it can learn from every new instance rapidly, even if the new instance is from a new class and it can handle incremental input features; a property that is essential when a new DNN is constructed and new input features appear in the fast memory.

1.5. Structure and contribution of the paper

The remainder of this paper is organized as follows. Section 2 reviews previous studies. Particularly, Section 2.4 provides an overview of various comparative models suggested for the online learning of DNNs. Section 3 introduces the general concept of DMA. Section 4 discusses the mGHN and its online learning method. Section 5 presents experimental results for the online learning of DNNs and analyzes the performance of the DMA. Section 5.1 explains the results for a non-stationary variant of the CIFAR-10 dataset, and Section 5.2 contains the description and the results for the Google Glass Lifelog dataset. Section 6 discusses the implication of the proposed architecture on other research fields, including CLS theory, Bayesian optimization, and lifelong learning.

This study is an extension of our previous work (Lee et al., 2016), which contributed the following to relevant literature: (1) Problem setup and review for the online learning of DNNs; (2) Proposal of the DMA and the mGHN; and (3) Empirical analysis of various online learning methods on real-life datasets. The main contributions of this study are: (1) Proof of the online parameter learning method of mGHNs; (2) Cognitive neuroscience perspective of DMA; (3) Making the Lifelog dataset publicly available; and (4) Implications of DMA on other machine learning fields. Moreover, additional empirical analysis and literature review are discussed in this study.

2. Related works

2.1. Deep learning and online learning

Deep learning algorithms, including CNNs and recurrent neural networks (RNNs), deliver state-of-the-art performance for various fields, including computer vision (He, Zhang, Ren, & Sun, 2015; Noh, Hong, & Han, 2015), speech recognition