Continual Learning summary

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Artificial Intelligence & Information Analysis Lab

Continual Lifelong Learning

- **Introduction**
- Regularization Methods.
- Dynamic Approaches.
- Complementary learning architectures.

What is Continual Lifelong Learning?

- The procedure when a machine learns many tasks.
- The ability of a machine to learn over a continuous stream of data.
- The ability to learn over non-stationary data distributions.
- Aims to gradually extend acquired knowledge.
- The ability to avoid **catastrophic forgetting**.
- Inspired by neuroscience and the ability of humans to manipulate knowledge and skills over their lifespan.

Why Continual Lifelong Learning?

- Crucial for machines that interact dynamically with the real world.
- Knowledge accumulation over many and various tasks.
- Learn over an extended period of time.
- Data is increasing at a huge rate, new topics appear everyday.
- Many applications on autonomous agents and robots.

Connection to Biology: Hebbian Plasticity & Stability

- As humans, we can absorb new knowledge and information without catastrophically forgetting previously acquired knowledge.
- This lifelong learning ability occurs while balancing the **plasticity – stability dilemma**.
- D.O. Hebb proposed the most well-known neuroscientific theory of the synaptic plasticity during the learning process.
- Plasticity is required in knowledge integration, while stability is needed in order to prevent the loss of previously acquired knowledge.

Stability – Plasticity dileimma

- Too much plasticity leads the previously encoded knowledge being overwritten by new information.
- Too much stability impedes the procedure of absorbing and encoding new information.
- When the stability – plasticity dilemma is balanced, humans can adapt new information and at the same time maintain old information.

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EWC Algorithm

- This algorithm maintains knowledge for a neural network in sequential task learning by a regularization approach.
- The solution to a new task is given without a big change on important weights for previous tasks.
- Important weights for each task are defined using the Bayes' Theorem.

Memory Aware Synapsis Model

- Given a neural network, Memory Aware Synapsis (MAS) model estimates the importance of the network's weights in an unsupervised way while learning a sequence of tasks. This estimation is based on the sensitivity function of the predicted output function.
- Goal: Knowledge has to be maintained or erased selectively, given the limited model capacity and the unlimited new information the model has to acquire.

MAS Model: Method

- Given a neural network with parameters $\theta_{i,j}$, MAS estimates the importance value $\Omega_{i,j}$ for each parameter $\theta_{i,j}$. The model receives a sequence of tasks T_n in the form of ordered pairs (X_n, Y_n). The task-specific loss L_n is combined with a regularizer that penalizes any change to the important parameters based on the sensitivity of the output predicted function.
- The process starts after the training of the T_1 task or using a pretrained model for that task.

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DEN Model

- Considers incremental learning of a DNN in a lifelong learning manner.
- It is used in sequential task learning.
- DEN dynamically controls its capacity.
- It performs selective training into data points that their weights are affected by the new task.
- It prevents catastrophic forgetting by splitting data points and then timestamp them.

DEN Model: Method

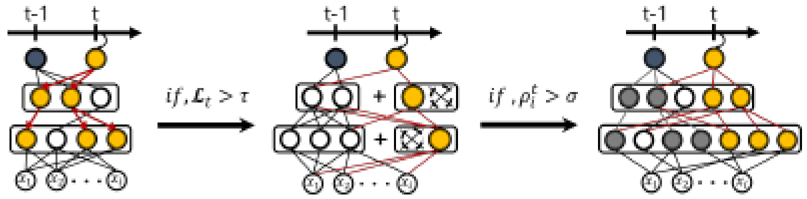
- Given a sequence of tasks $t = \{1,2,\dots,T\}$, the task t comes with data $D_t = \{(\boldsymbol{x}_i, y_i)\}_{i=1}^{N_t}$.
- In terms of simplicity, the analysis will refer to the classification task for two classes.
- The problem is stated as:

$$min_{W^t} L(\boldsymbol{W}^t; \boldsymbol{W}^{t-1}, D_t) + \lambda\Omega(\boldsymbol{W}^t) \quad for\ t = 1, \dots \qquad (1)$$

where L is the task specific loss, $\boldsymbol{W}^t = \{\boldsymbol{W}_l\}_{l=1}^{L}$ the weight tensor and Ω a regularizer.

DEN Model: Method

- DEN also timestamp each added unit, in both expansion and split procedures, to record the training stage when this addition happens.
- In this way, the ability of the network to prevent catastrophic forgetting strengthens.



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FearNet Model

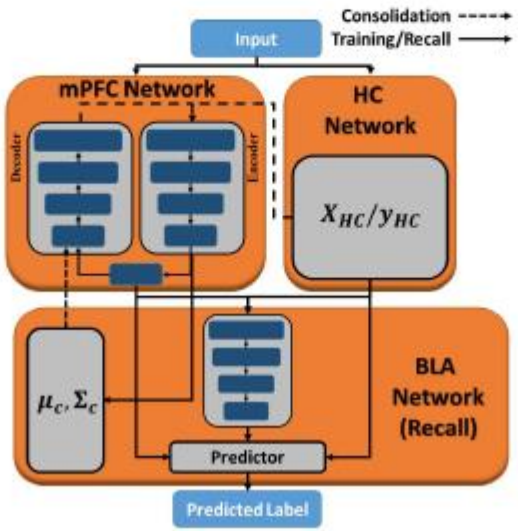
Inspired by brain science, FearNet is a generative model and uses a dual memory system for knowledge absorption and maintenance.

- A short - term memory system for new information (HC network)
- A long – term memory system for recall (mPFC, deep neural network)

Inside its architecture lies a module (BLA network) that determines which memory center is used for prediction.

FearNet Model

where $\psi = \left(1 - \mathrm{A(x)}\right)^{-1} max_k P_{HC}(C = k|x)A(x) \in [0,1]$, is a probability that determines if the instances of the class k are actually stored in HC.



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Q & A

Thank you very much for your attention!

More material in
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