CONTINUAL LEARNING

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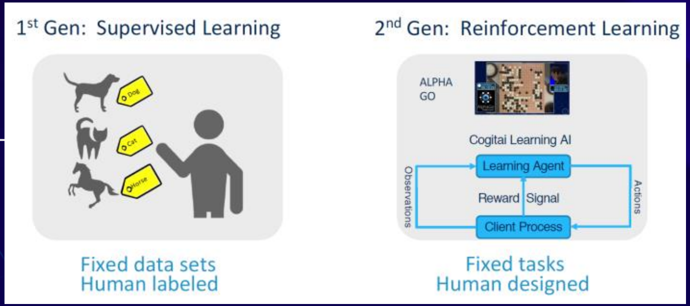
INTRODUCTION

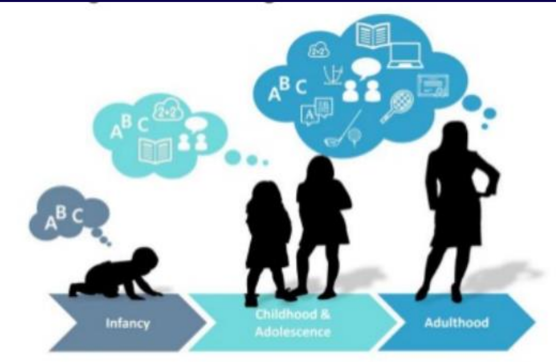
The ability to continually learn over time by accommodating new knowledge while retaining previously learned experiences is referred to as continual or lifelong learning.

It also focuses on learning adaptively about the external world and enabling the autonomous incremental development of ever more complex skills and knowledge.


CONTINUE LEARNING


1st Gen: Supervised Learning
Fixed data sets
Human labeled
2nd Gen: Reinforcement Learning
ALPHA GO
Cogitai Learning AI
Learning Agent
Reward Signal
Client Process
Observations
Actions
Fixed tasks
Human designed


ABCDEFGHIJKLMNOPQRSTUVWXYZ
Hello!
Bonjour!
你好!
Hola!


Infancy
Childhood & Adolescence
Adulthood

CONTINUAL LEARNING

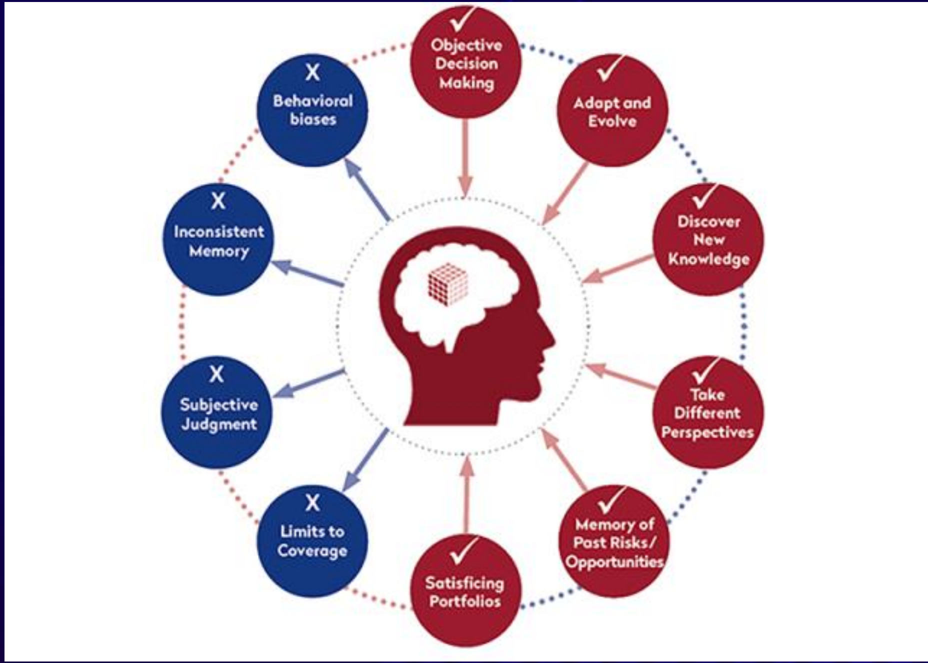
Humans become increasingly smarter over time. This has been possible due to continual learning adaptability.

1. Tasks are received in a sequential order.

2.Knowledge is transferred from previously Learned tasks.

3.New knwoledge is stored for future use.

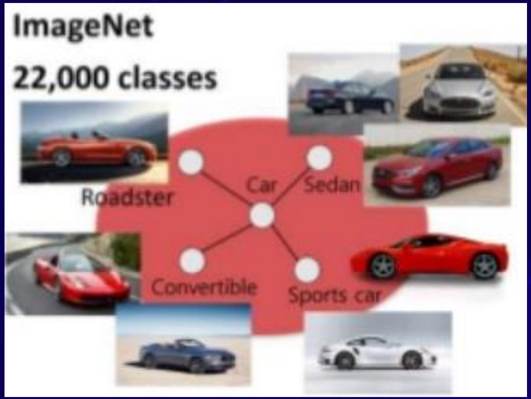
4.Refine existing knowledge.

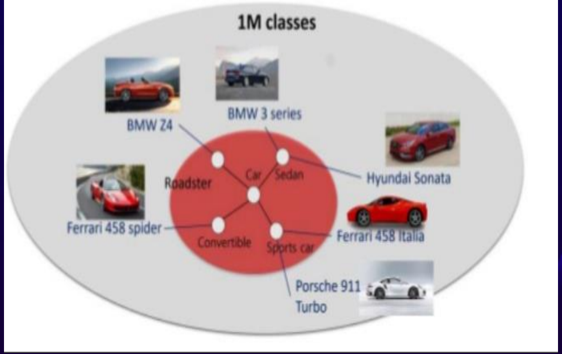


CHALLENGES

01 INCOMPLETE

In many large-scale learning scenarios, not all training data might be availabel when we want to begin training the network.



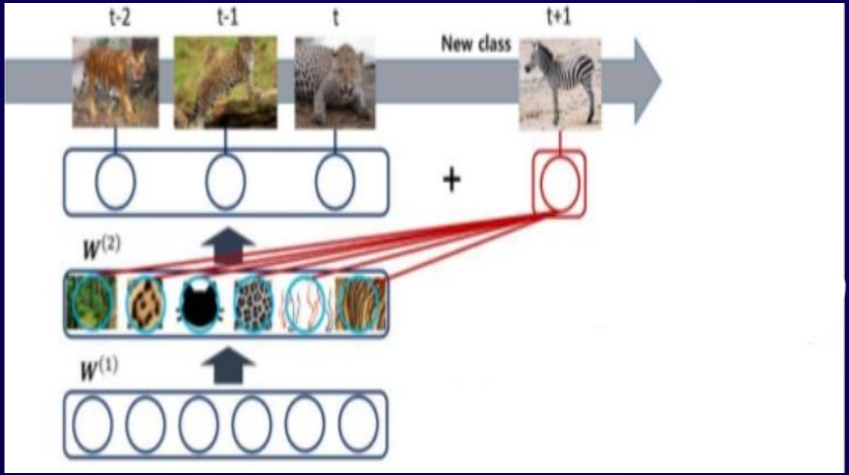


02 GROWING DATASET

Even worse, the set of tasks may dynamically grow as new tasks are introduced.

CHALLENGES

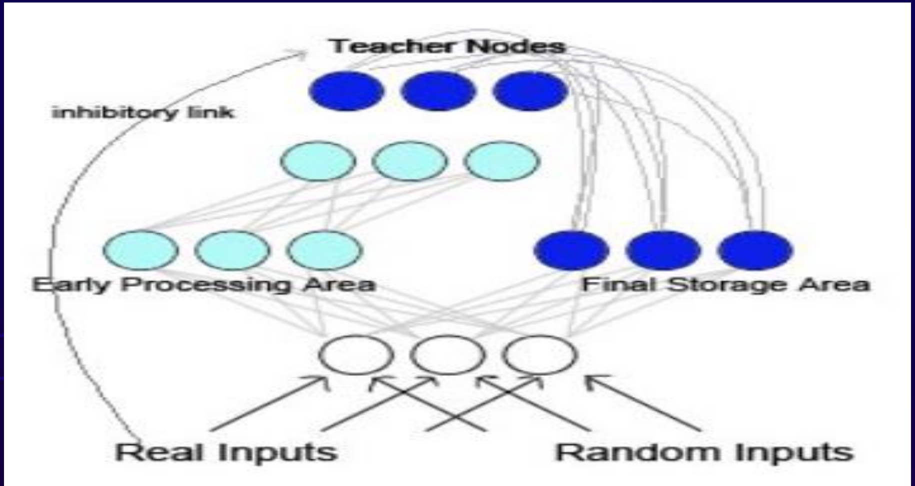
However, if the classes we had in the early stages of learning significantly differs from the new class, utilization of prior knowledge may degenerate performance.



The weight of models could significantly change to classify the zebra.

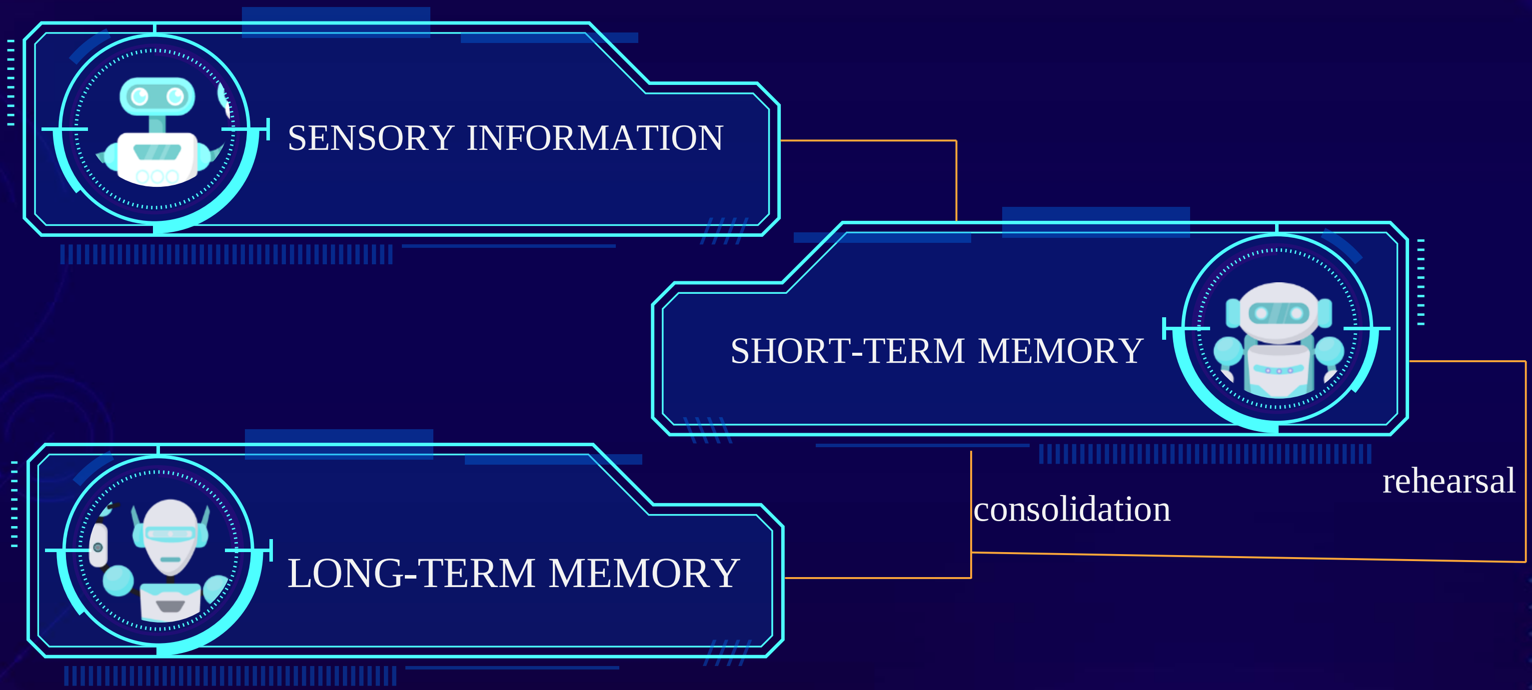
CATASTROPHIC LEARNING

When training on new tasks or categories, a neural network tend to forget the information learned in the previous trained tasks. This usually means a new task will likely override the weights that have been learned in the past, and thus degrade the model performance for the past tasks.



SOLUTIONS

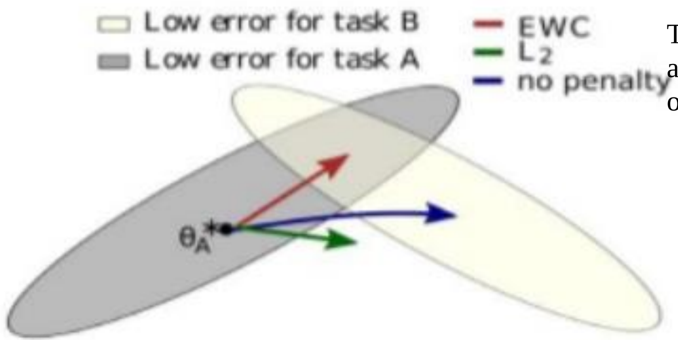
SYNAPTIC CONSOLIDATION → Mammalian brain may avoid catastrophic forgetting by protecting previously acquired knowledge in neocortical circuits.



Acquired knowledge is durably encoded in synapses that are rendered less plastic thus stable, called synaptic consolidation.

ELASTIC SOLID CONSOLIDATION

In brains, synaptic consolidation enables continual learning by reducing the plasticity of synapses that are vital to previously learned tasks. We implement an algorithm that performs similar operation in artificial convolution neural networks constraining the important parameters to stay close to old values.



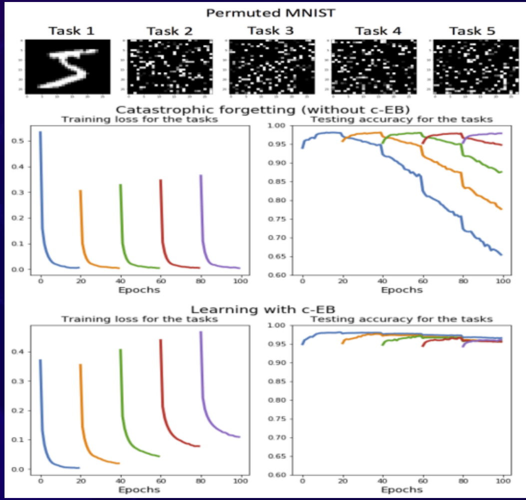
This[L(ɵ)] loss function not only care about loss of Task B but also performance of Task A

$$\mathcal{L}(\theta) = \underbrace{\mathcal{L}_B(\theta)}_{\text{Task B loss}} + \underbrace{\sum_i \frac{\lambda}{2} F_i(\theta_i - \theta^*_{A,i})^2}_{\text{Transfer Constraints}}$$

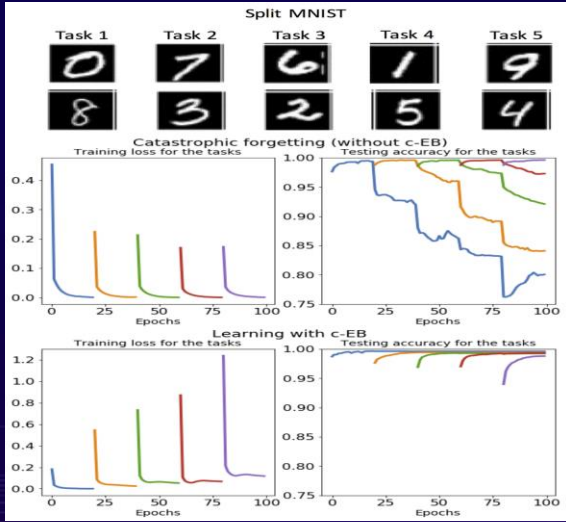
EWC protects the performance in task A by constraining the parameters to stay safe in a region of low error for task, where is around ɵ

BENCHMARK FOR CF

PERMUTED MNIST



SPLIT MNIST



REFERENCES

[1]. AGHASI, A., ABDI, A., NGUYEN, N., AND ROMBERG, J. Net-trim: Convex pruning of deep neural networks with performance guarantee. In Advances in Neural Information Processing Systems (2017), pp. 3180–3189.

[2]. AHMED, K., BAIG, M. H., AND TORRESANI, L. Network of experts for large-scale image categorization. In Computer Vision – ECCV 2016 (Cham, 2016), B. Leibe, J. Matas, N. Sebe, and M. Welling, Eds., Springer International Publishing, pp. 516–532.

THANK YOU!