

Continual Lifelong Learning



Jonas Wildberger
University of Oxford

Problem Description

- Machine vs. Human learning

- Catastrophic Forgetting

- Overcoming Catastrophic Forgetting

Elastic Weight Consolidation

Continual Learning Through Synaptic Intelligence

Comparison and Outlook

- Experiments

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- ▶ State-of-the art ANNs rival human performance in a variety of domain-specific tasks

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How do we enable learning in an online fashion for ANNs?

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Problem: Minimise total loss function without access to loss function of previous tasks

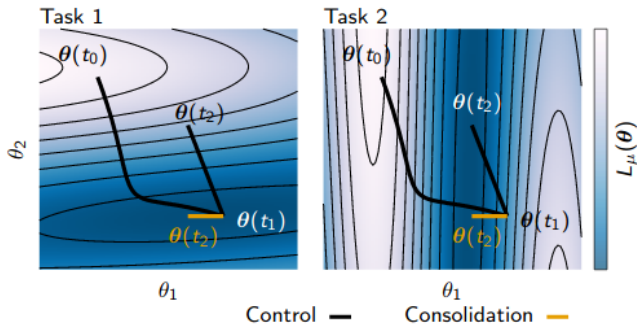


Figure: Illustration of Catastrophic Forgetting [ZPG17]

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2. Functional approach

- ▶ Add regularisation term that penalises changes in input-output function, i.e. predictions are similar across tasks
- ▶ Computationally expensive: For every new data point, compute forward pass through old task's network

3. Structural approach

- ▶ Penalties on the parameters s.t. they remain close to values for old task
- ▶ Mimic complexity of biological synapses
- ▶ Retain task relevant information and measure of importance

Elastic Weight Consolidation

Let $\mathcal{D}_A, \mathcal{D}_B$ be two independent tasks $\mathcal{D}_A \cup \mathcal{D}_B = \mathcal{D}$

$$\log p(\theta|\mathcal{D}) = \log p(\mathcal{D}|\theta) + \log p(\theta) - \log p(\mathcal{D}) \quad (1)$$

Independence of $\mathcal{D}_A, \mathcal{D}_B$ gives

$$\log p(\theta|\mathcal{D}) = \underbrace{\log p(\mathcal{D}_B|\theta)}_{=-\mathcal{L}_B} + \log p(\theta|\mathcal{D}_A) - \log p(\mathcal{D}_B) \quad (2)$$

All information (including which parameters are important) about task A absorbed in posterior $p(\theta|\mathcal{D}_A)$.

$$\mathcal{L}(\theta) = \mathcal{L}_B(\theta) + \sum_i \frac{\lambda}{2} F_i (\theta_i - \theta_{A,i}^*)^2 \quad (3)$$

λ : Compares importance of task A to task B , F_i : Diagonal of Fisher information matrix

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- Posterior $p(\theta|\mathcal{D}_A)$ approximated by F
- Iteratively applicable to more than 2 tasks

Continual Learning Through Synaptic Intelligence

How does learning task k change the total loss? Let $\mathbf{g} = \partial_{\boldsymbol{\theta}} \mathcal{L}$:

$$\int_C \mathbf{g}(\boldsymbol{\theta}(t)) d\boldsymbol{\theta} = \int_{t_0}^{t_1} \mathbf{g}(\boldsymbol{\theta}(t)) \cdot \boldsymbol{\theta}'(t) dt \quad (4)$$

$$= \sum_{\mu} \sum_k \int_{t^{\mu-1}}^{t^{\mu}} g_k(\boldsymbol{\theta}(t)) \theta'_k(t) dt \quad (5)$$

$$= - \sum_{\mu} \omega_k^{\mu} \quad (6)$$

ω_k^{μ} contribution of μ th task and k th parameter to change in total loss

- Update ω_k^μ online as running sum

$$\sum_t \partial_{\theta_k} \mathcal{L}(t) \cdot \partial_t \theta_k(t)$$

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For current task μ :

$$\Omega_k^\mu = \sum_{\nu < \mu} \frac{\omega_k^\nu}{(\Delta_k^\nu)^2 + \xi} \quad (7)$$

$$\tilde{\mathcal{L}}_\mu(\theta) = \mathcal{L}_\mu(\theta) + c \underbrace{\sum_k \Omega_k^\mu (\theta_k(t^{\mu-1}) - \theta_k)^2}_{\text{surrogate loss}} \quad (8)$$

c strength parameter trading off old vs. new memories

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- ▶ Surrogate loss approximates summed loss functions of previous tasks
 - ▶ Same minimum as previous parameter configuration
 - ▶ Same ω_k^{ν} over Δ_k

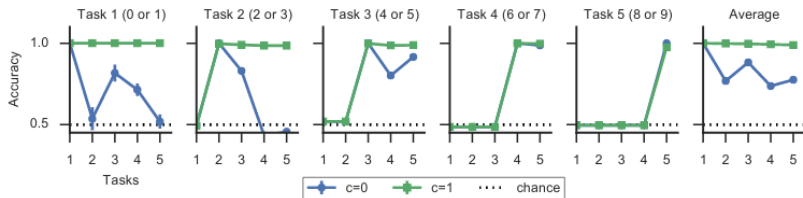
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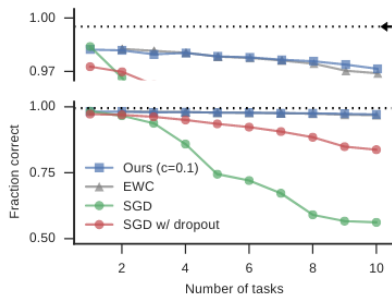
- ▶ Surrogate loss approximates summed loss functions of previous tasks
 - ▶ Same minimum as previous parameter configuration
 - ▶ Same ω_k^{ν} over Δ_k
- ▶ Derivation only valid for two task; but empirically works for more

Comparison and Outlook

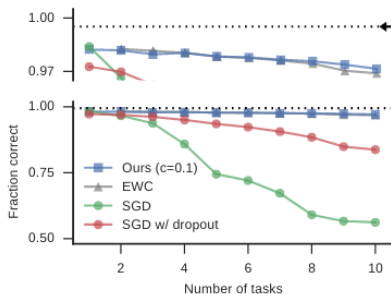
- Divide MNIST into 5 subsets of consecutive digits; learn to distinguish between two consecutive digits



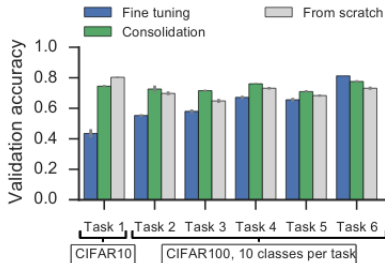
- ▶ Randomly permute all MNIST pixels for a task
- ▶ Performance measured by correctness across all tasks



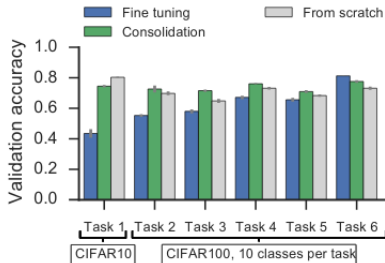
- ▶ Randomly permute all MNIST pixels for a task
- ▶ Performance measured by correctness across all tasks
- ▶ Correlations of ω_k^μ decrease across different tasks μ :
"Using different weights to learn new tasks"



- First image classification on CIFAR-10, then 5 additional tasks corresponding to 10 consecutive classes from CIFAR-100



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- ▶ Better validation accuracy than networks trained on single task only: Less prone to overfitting



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- ▶ EWC:
 - ▶ Offline, point estimate of posterior probability
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- ▶ Synaptic Intelligence
 - ▶ Online estimate over entire learning trajectory
 - ▶ Doesn't scale naturally to multiple tasks

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- ▶ Can we cluster important weights and use other sparsity regularisation strategies such as group Lasso?

In addition to adding depth to our networks, we may need to add intelligence to our synapses.



Friedemann Zenke, Ben Poole, and Surya Ganguli.
Continual learning through synaptic intelligence, 2017.