Continual Lifelong Learning

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Outline

Problem Description

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

Catastrophic Forgetting

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

Catastrophic Forgetting II

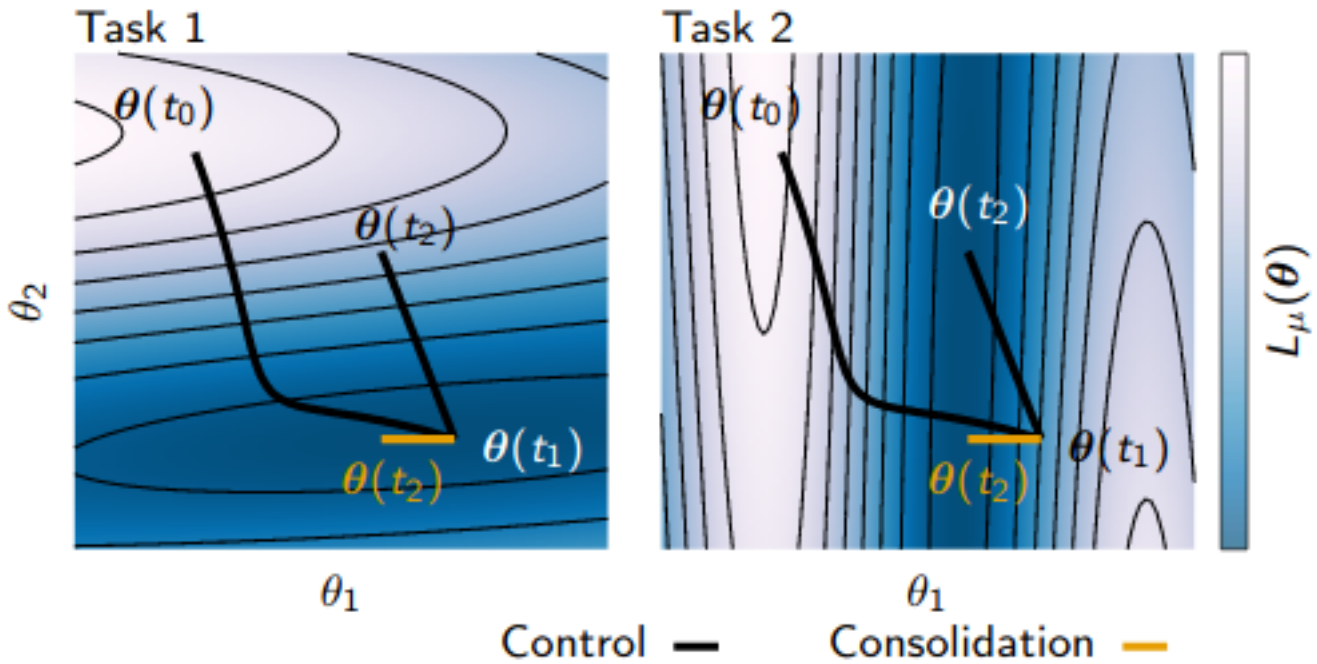

Figure: Illustration of Catastrophic Forgetting [ZPG17]

Overcoming Catastrophic Forgetting I

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   - Alter architecture of network, e.g. freezing weights, changing learning rate for layers shared with original task, feature augmentation
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 $\mathcal{D}_A \cup \mathcal{D}_B = \mathcal{D}$ with learned parameters θ_A, θ_B:

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

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

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

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

Loss function

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

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 $\boldsymbol{g} = \partial_{\boldsymbol{\theta}} \mathcal{L}$:

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

$$= \sum_{\mu} \sum_{k} \int_{t^{\mu-1}}^{t^{\mu}} g_k(\theta(t)) \theta_k'(t) dt \tag{5}$$

$$= -\sum_{\mu} \omega_k^{\mu} \tag{6}$$

ω_k^{μ} contribution of μth task and kth parameter to change in total loss

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- Update ω_k^μ online as running sum

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  1. contribution of θ_k to drop in Loss ω_k^ν
  2. How much it changed $\theta_k(t^\nu) - \theta_k(t^{\nu-1}) = \Delta_k^\nu$

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  For current task μ:

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

Loss function

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

c strength parameter trading off old vs. new memories

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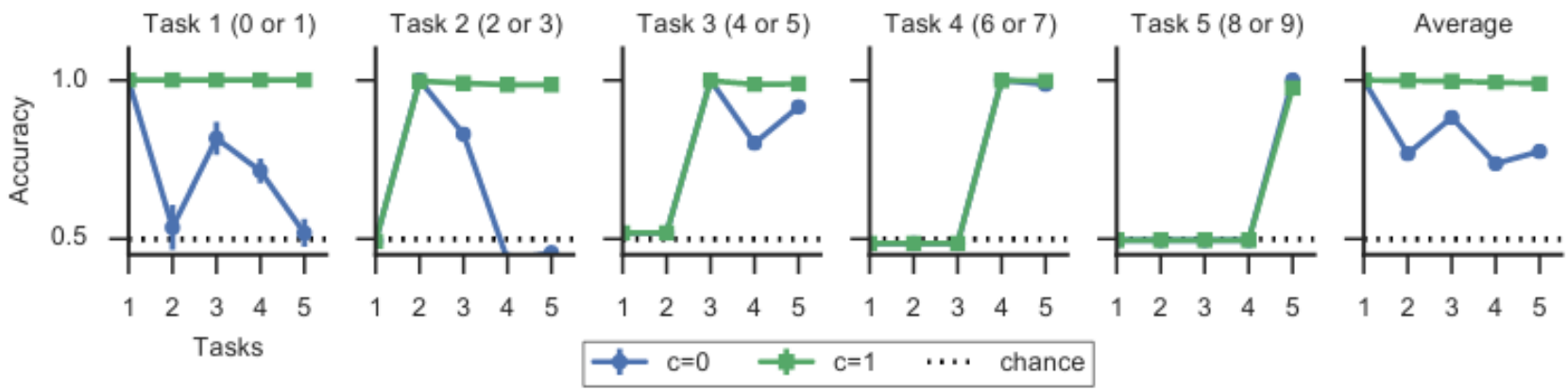
c strength parameter trading off old vs. new memories

- 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

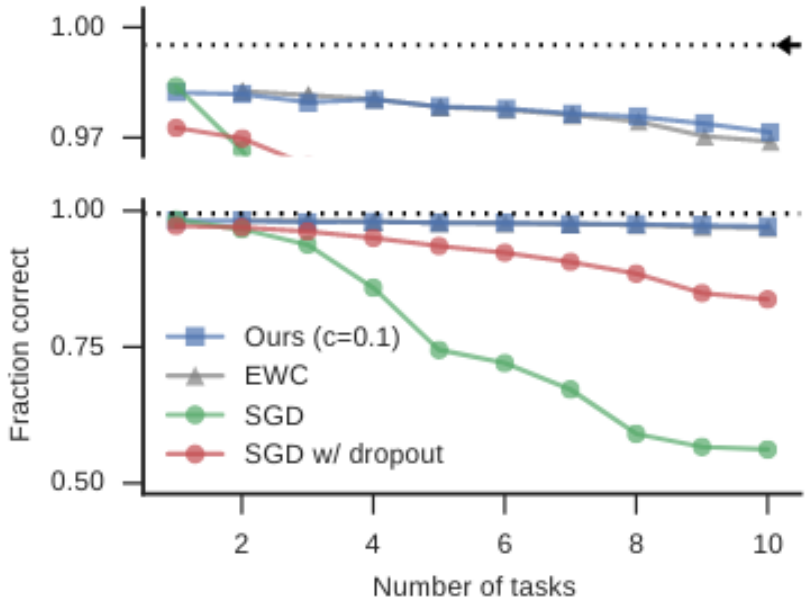
Split MNIST

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



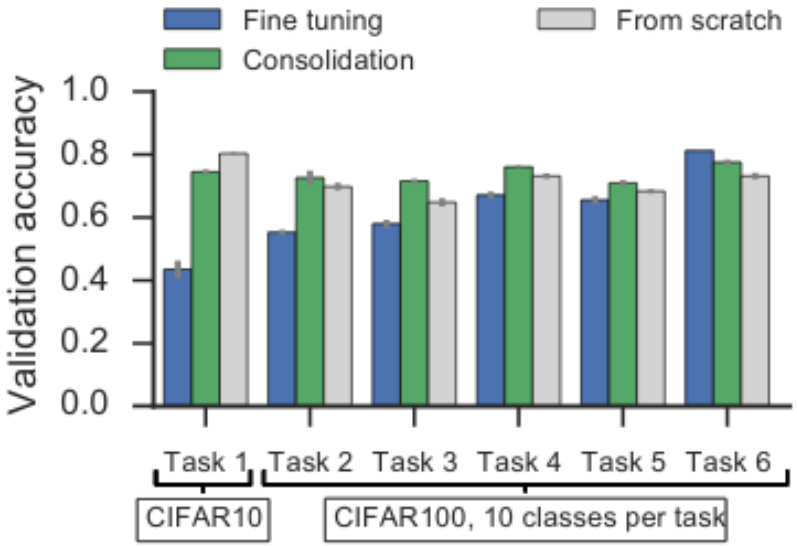
Permuted MNIST

- 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"



Split CIFAR-10/CIFAR-100

- First image classification on CIFAR-10, then 5 additional tasks corresponding to 10 consecutive classes from CIFAR-100
- 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
  - Computing diagonal of Fisher has linear complexity in number of data points
- Synaptic Intelligence
  - Online estimate over entire learning trajectory
  - Doesn't scale naturally to multiple tasks

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- Fixing the hyperparameters λ, c is quite expensive. Can we adaptively learn or predict them based on a priori knowledge about new task?
- 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.

References


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