Continual Learning and Catastrophic Forgetting

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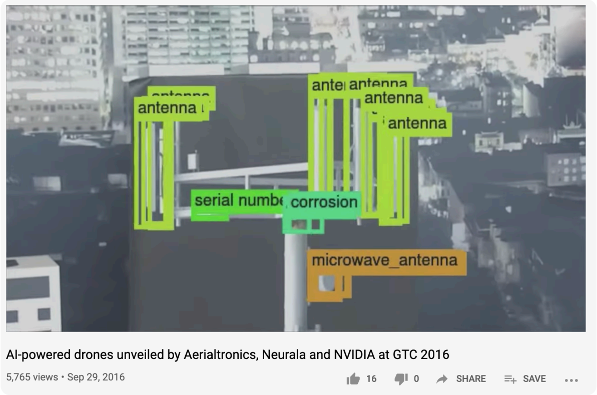
Outline:

- Context + initial approaches
- Evaluating algorithms
- Algorithms for CL

Example context for continual learning



AI-powered drones unveiled by Aerialtronics, Neurala and NVIDIA at GTC 2016

5,765 views • Sep 29, 2016

Other example: autonomous vehicles

What are examples of situations where continual learning is desirable?

Can you simply train on new data?

Task A: $D_A = \{(x_i, y_i)\}$ Task B: $D_B = \{(x_i, y_i)\}$

First,

$$\min_{\theta} \sum_{x_i, y_i \in D_A} L(\hat{y}_\theta(x_i), y_i)$$ initialize randomly

Then,

$$\min_{\theta} \sum_{x_i, y_i \in D_B} L(\hat{y}_\theta(x_i), y_i)$$ initialize w/ soln to above task

Failure mode: catastrophic forgetting / interference

Typically, good performance at B
worse performance at A

Visualization in parameter space of catastrophic forgetting

Demonstration of catastrophic forgetting using linear regression in 2-d

$D_A = \{ (\begin{pmatrix} 1 \\ 0 \end{pmatrix}, 1) \}$

$D_B = \{ (\begin{pmatrix} 1 \\ 1 \end{pmatrix}, 2) \}$

$y = (1 \ 1) \cdot x$

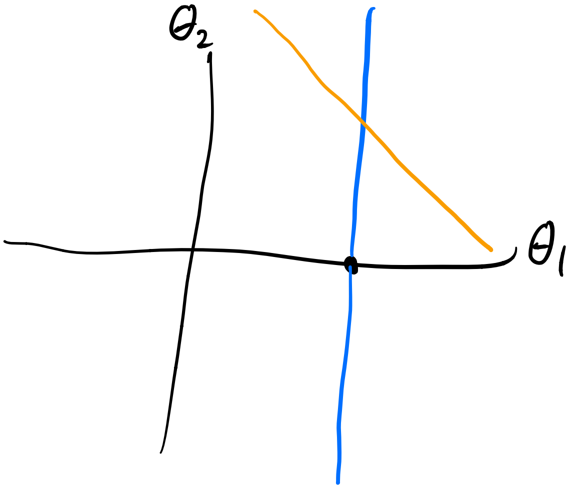
true response

Model: $y = x^t \theta + \varepsilon$

Linear regression

$$\min_{\theta} \| y - x^t \theta \|^2$$ inialized at $\theta = \theta_0$

Soln $\theta = P_{y = x^t \theta} \theta_0$



How can you mitigate forgetting?

Train from scratch w/ new data and old data

Drawbacks

- Many industry nets take days – weeks to train
- Waste of power and compute
- Original training data may be unavailable

When might original training data be unavailable?

- Need access to GPUs / Cloud / steady internet

When would cloud/gpu access be an issue?

Humans can learn incrementally, so it is possible to do

Replay old training data w/ new data

- requires storing old data
- Storage costs grow linearly w/ tasks

Dilemma: plasticity – stability

Reviews: Parisi et al. 2019

Chen and Liu 2018

Evaluating Continual Learning Algorithms

(Kemker et al. 2017)

Data permutation tasks

Task 1: Training data ~ MNIST $(\overset{\text{img}}{X_i}, \overset{\text{class } 0-9}{y_i})$

Given X_i, predict y_i

Task 2: Fix an image permutation P_2

Training data ~ MNIST $(P_2 X_i, y_i)$

Given $P_2 X_i$, predict y_i

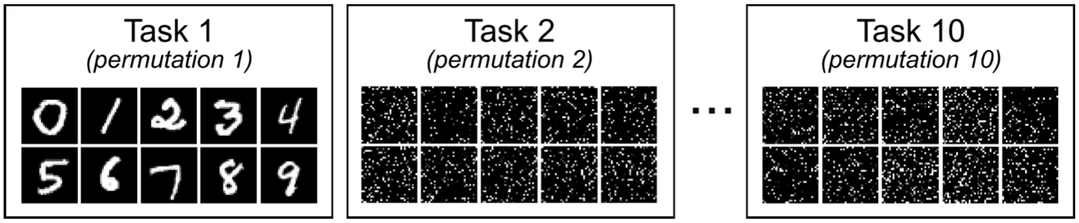


Figure 2: Schematic of permuted MNIST task protocol.

(Van de Ven and Tolias 2019)

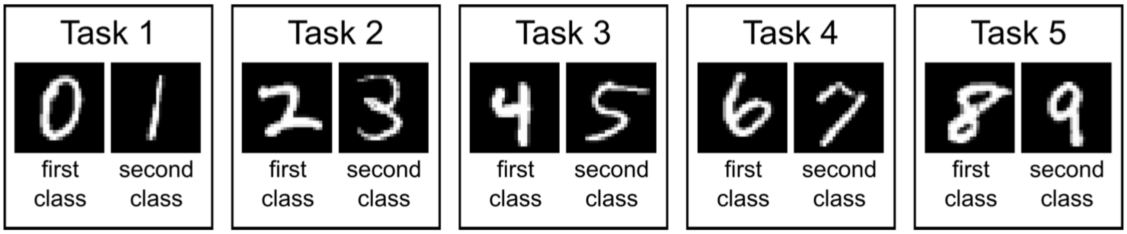
Comments:

Each task is equally difficult

When/why are these tasks equally difficult?

Incremental Class learning

Learn a base task set, then learn additional classes



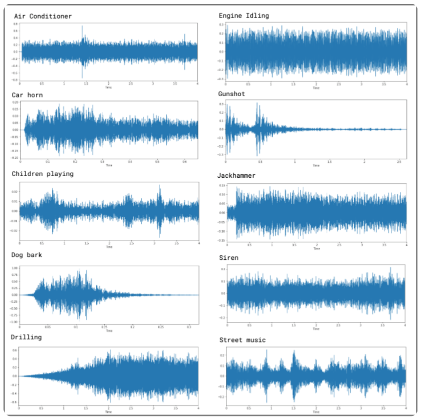
(Van de Ven and Tolias 2019)

Shared features w/ new classes

Are these tasks equally difficult?

Multimodal learning

Learn an image classification task
then learn audio classification



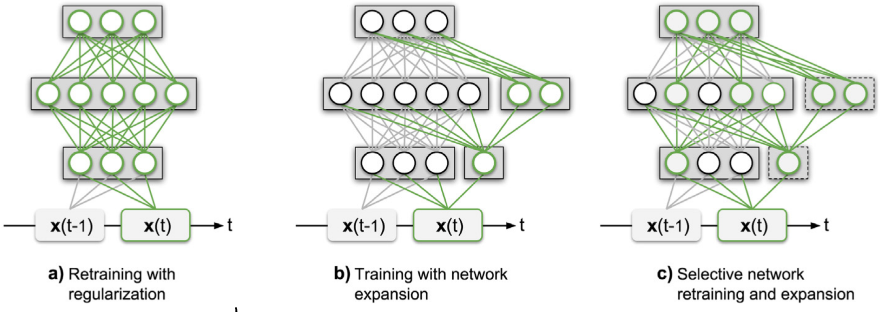
Different features must be learned

Approaches for continual learning

- Train whole net w/ regularization
- Dynamic architectures (add neurons)
- Complementary Learning Systems (memory + replay)

(and more)

G.I. Parisi, R. Kemker, J.L. Part et al. / Neural Networks 113 (2019) 54–71



a) Retraining with regularization

b) Training with network expansion

c) Selective network retraining and expansion

regularization

dynamic architectures

Regularization approaches

Update network weights but penalize changes in order to minimize forgetting

(Li + Hoiem 2018)

Learning without Forgetting (LwF)

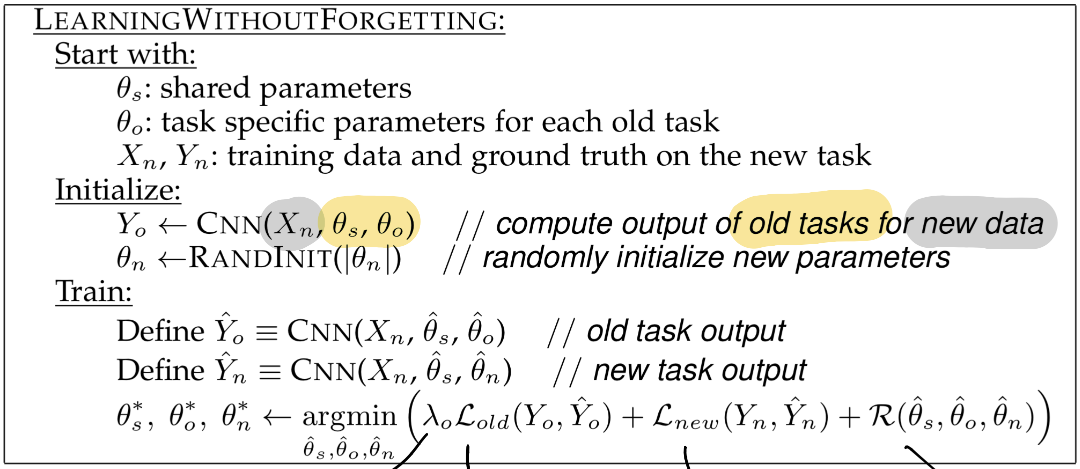
Consider predictor with shared parameters across tasks and some task specific parameters

At new task, update:

shared params, new params, AND old params

So that

output of old task on new data doesnt change too much.



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LEARNINGWITHOUTFORGETTING:
  Start with:
      $\theta_s$: shared parameters
      $\theta_o$: task specific parameters for each old task
      $X_n, Y_n$: training data and ground truth on the new task
  Initialize:
      $Y_o \leftarrow \mathrm{CNN}(X_n, \theta_s, \theta_o)$     // compute output of old tasks for new data
      $\theta_n \leftarrow \mathrm{RANDINIT}(|\theta_n|)$     // randomly initialize new parameters
  Train:
      Define $\hat{Y}_o \equiv \mathrm{CNN}(X_n, \hat{\theta}_s, \hat{\theta}_o)$     // old task output
      Define $\hat{Y}_n \equiv \mathrm{CNN}(X_n, \hat{\theta}_s, \hat{\theta}_n)$     // new task output
      $\theta_s^*, \theta_o^*, \theta_n^* \leftarrow \operatorname{argmin}_{\hat{\theta}_s, \hat{\theta}_o, \hat{\theta}_n} \left(\lambda_o \mathcal{L}_{old}(Y_o, \hat{Y}_o) + \mathcal{L}_{new}(Y_n, \hat{Y}_n) + \mathcal{R}(\hat{\theta}_s, \hat{\theta}_o, \hat{\theta}_n)\right)$
```

parameter for plasticity-stability

modified cross-entropy loss

cross-entropy loss

weight decay

Note: does not require seeing old data!

Why optimize the task specific parameters for the previous task instead of leaving them fixed?

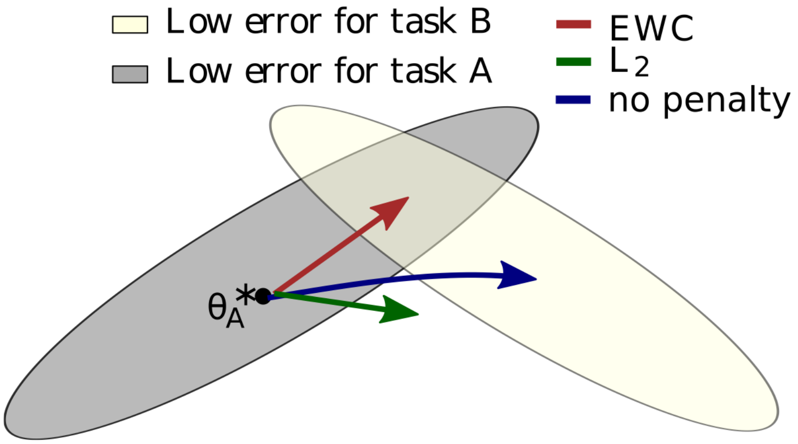
Learning without forgetting is a “regularization” based method for continual learning. Where is the regularization?

Elastic Weight Consolidation (EWC)

(Kirkpatrick et al. 2017)

When training on task B, identify weights that were important to A and penalize updates to those weights

Try to stay in low error region for A



Minimize

parameter

Solution to task A

$$L(\theta) = L_B(\theta) + \sum_i \frac{\lambda}{2} F_i \left(\theta_i - \theta^*_{A,i}\right)^2$$

where

$$F_i = \mathbb{E}_x \left(\partial_{\theta_i} \log p_\theta(x)\right)^2$$

diagonal entry of Fisher information matrix of predictor at θ_A^*

How does this figure compare to the catastrophic forgetting visualization above?

Motivated by a Bayesian learning perspective

What is Bayesian learning?

$(x_i, y_i) \sim$ dist Of data iid

$D = \{(x_i, y_i)\}_{i=1 \dots n}$

model : $x \mapsto$ distribution on y params θ

$\max_\theta P(D|\theta)$ vs. $\max_\theta P(\theta|D)$

MLE

MAP

max a posteriori estimation

frequentist

prior $p(\theta)$

collect D

update prior $p(\theta|D)$

Bayesian

Bayes Theorem:

$$\underbrace{\log p(\theta|D)} = \underbrace{\log P(D|\theta)} \underbrace{+ \log P(\theta) - \log P(D)}$$

If $p(\theta) \equiv \text{const} \Rightarrow$ equivalent MLE $\Leftrightarrow$ MAP

uninformative prior

Does there exist a prior $p(\theta)$ uninformative over $\mathbb{R}^d$?

Improper prior

Example of Bayesian perspective on learning:

MLE training of a NN — MAP Estimation w/ noninformative. improper prior

Weight Decay

$$\min_{\theta} \; -\log P(D|\theta) + \|\theta\|_2^2$$

Bayesian perspective: prior $\log P(\theta) = -\|\theta\|_2^2$

$$P(\theta) \sim N(0, I)$$

Derivation of Fisher Information

Dist $p(x|\theta)$ $p_\theta(x)$

How sensitive is it to changes in θ?

$\nabla_\theta \log p(x|\theta) = 0$ at a soln to training

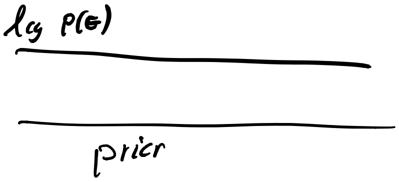
Instead, look at $D^2_\theta \log p(x|\theta)$

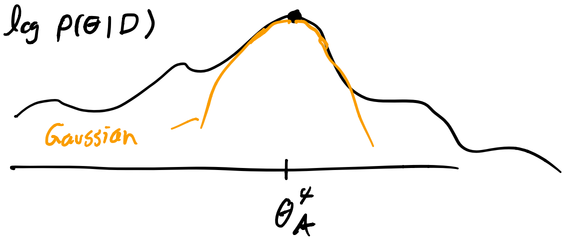
$$\mathbb{E}_{x\sim p_\theta} D^2_\theta \log p(x|\theta) = \underbrace{\mathbb{E}_{x} \nabla \log p(x|\theta) \nabla \log p(x|\theta)^t}_{\text{Fisher Information of } p_\theta}$$

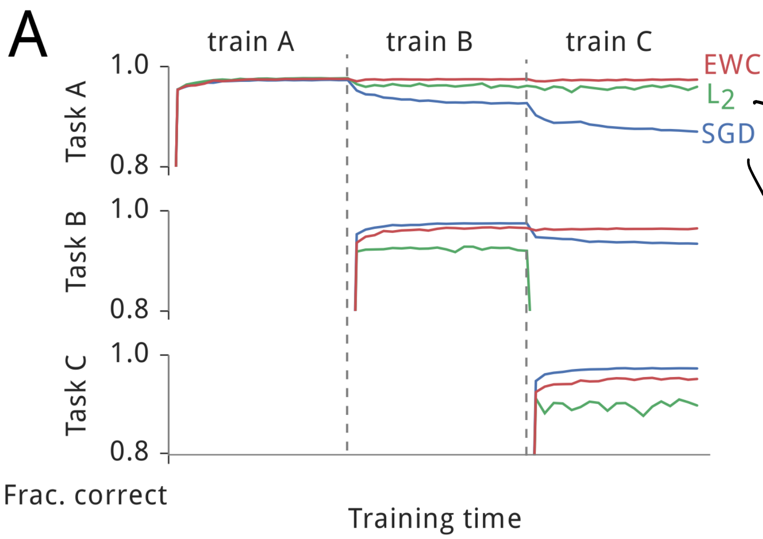
large diagonal entries have large information content

Fisher info is covariance^{-1} of $\nabla \log p$

Fisher Information Matrix provides locally Gaussian approximation to a posterior distribution







penalize θ_i by Fisher information

penalize all θ_i equally

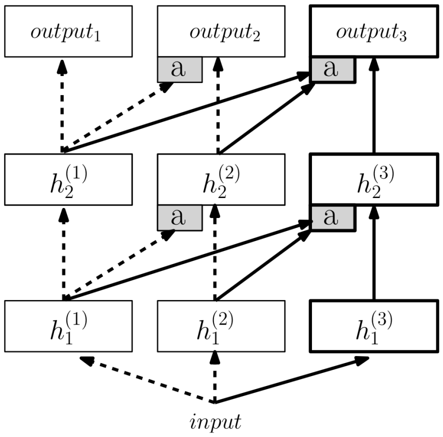
just train on new data

Progressive Neural Networks

(Rusu et al. 2016)

For each new task,

- add neurons
- add output layer
- add lateral connections
- dont modify old weights

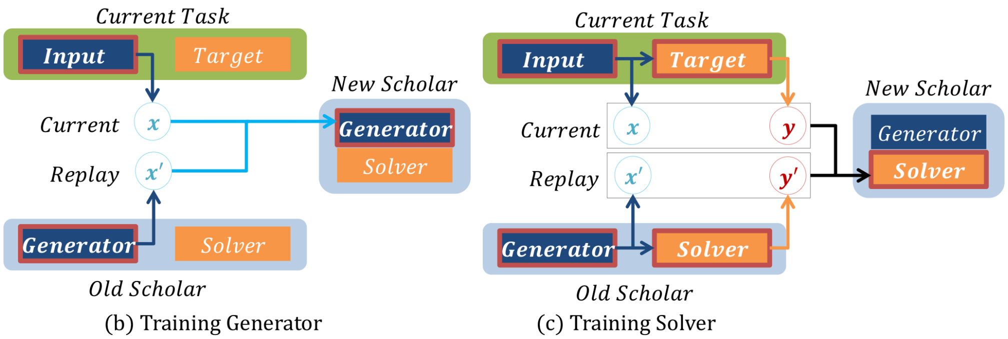


Generative Replay

(Shin et al. 2017)

Train a generative model to output synthetic data that follows same distribution as training data.

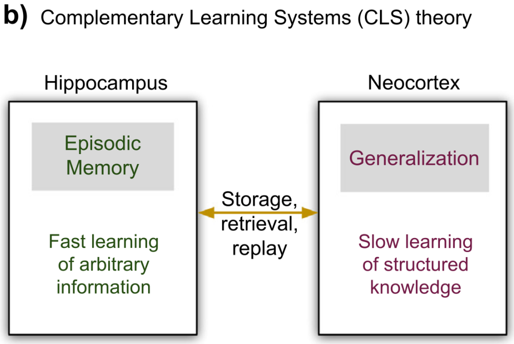
Replay synthetic data along w/ new data



(b) Training Generator

(c) Training Solver

Takes inspiration from human learning


b) Complementary Learning Systems (CLS) theory
Hippocampus
Episodic Memory
Fast learning of arbitrary information
Storage, retrieval, replay
Neocortex
Generalization
Slow learning of structured knowledge

(Parisi et al 2019)

Does generative replay avoid the data storage concerns that motivated continual learning methods?

Does generative replay avoid the data privacy concerns that motivated continual learning methods?