NANYANG TECHNOLOGICAL UNIVERSITY
School of Computer Science and Engineering

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Lifelong Object Recognition using Regularization and Data Augmentation

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1. Problem Statement

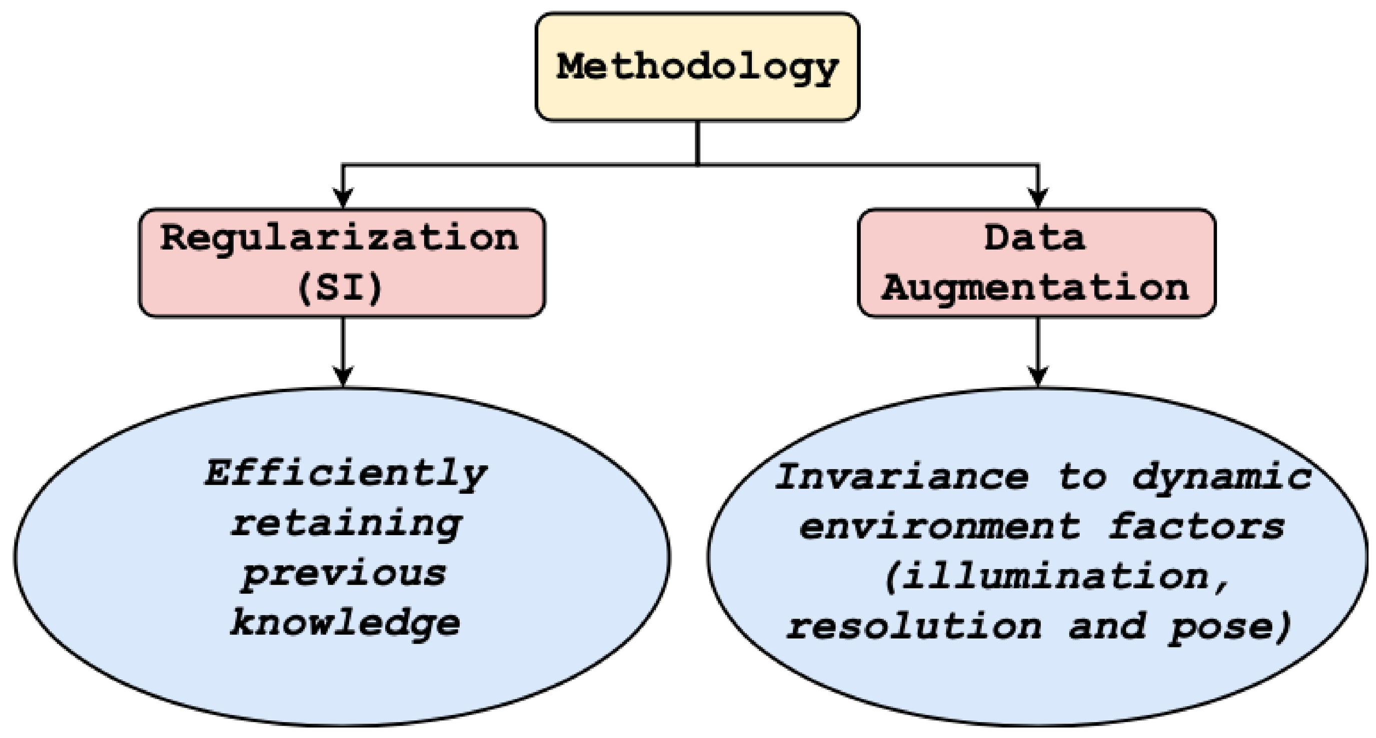
- Perform ***Lifelong Learning***, when faced with ***difficulty-incremental learning*** scenario with changing environmental conditions.
- The objectives are,
  - Efficiently retain previous knowledge acquired
  - Leverage past knowledge to generalize to new tasks

  when continuously learning under difficulty-incremental environmental conditions such as ***occlusion, illumination, clutter, pose***, etc.

2. Proposed Method

The proposed method uses

- ***Regularization*** based approach to efficiently retain previous knowledge
- ***Data augmentation*** tackle *data imbalance* and *invariance* to dynamic environment factors



3. Regularization based Lifelong Learning

(Continual Learning through Synaptic Intelligence (ICML 2017) F. Zenke, et al.)

- Regularization based Lifelong approaches broadly can be categorized under
  - Protecting parameters important for previous tasks
    - **EwC** (J. Kirkpatrick, et al. 2016)
    - **SI** (F. Zenke, et al.**,** 2017)
  - Knowledge Distillation based methods
    - **LwF** (Z. Li et al 2016)
- We use ***'Synaptic Intelligence'***, based regularization for preserving parameters important for previously acquired knowledge.
- Here, the loss term is augmented with an extra loss reflecting the importance of parameters

$$\tilde{L}_\mu = L_\mu + c\underbrace{\sum_k \Omega_k^\mu \left(\tilde{\theta}_k - \theta_k\right)^2}_{\text{surrogate loss}}$$

- The importance of a parameter ($\boldsymbol{\Theta}_{\mathbf{k}}$) for a task ($\boldsymbol{v}$), is a measure of two quantities
  - Contribution of that parameter to the drop in loss over entire training trajectory ($\boldsymbol{w}_{\boldsymbol{k}}^{\boldsymbol{v}}$)
  - Change of parameter, after training on task $\boldsymbol{v}$. ($\boldsymbol{\Delta}_{\boldsymbol{k}}^{\boldsymbol{v}}$)

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

4. Data Augmentation

Data augmentation is used to tackle the *data imbalance problem* and improve generalization of the model, to *prevent overfitting* of the model.

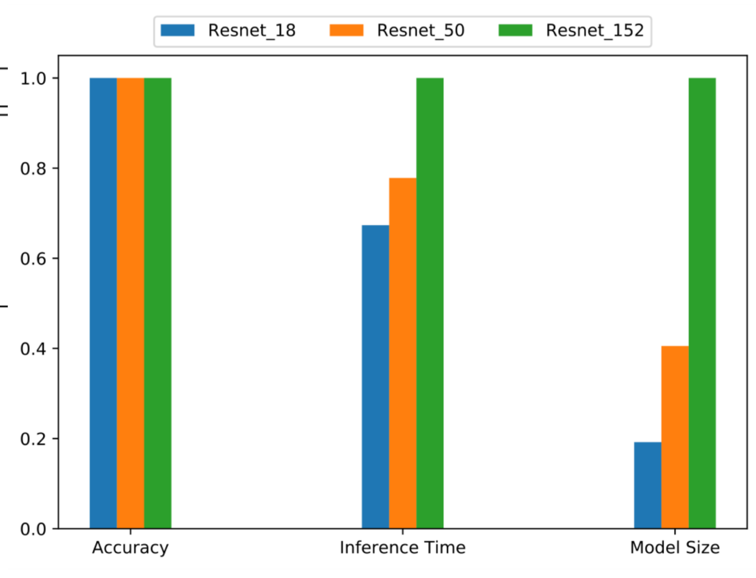
The following are the data augmentations used along with the intended invariances expected to be achieved.

Image Augmentation	Configuration	Purpose
Color Jitter	*Random brightness & contrast ((b : 0.5,1), (c : 0.5, 2))*	Illumination invariance
Gaussian Blur	*mean = 0, std. dev = 0.3, p=0.1*	Resolution invariance
Random Affine	*degrees = +/- 10*	Camera Pose invariance
Horizontal Flip	*p = 0.2*	Camera Pose invariance

5. Experimental Results

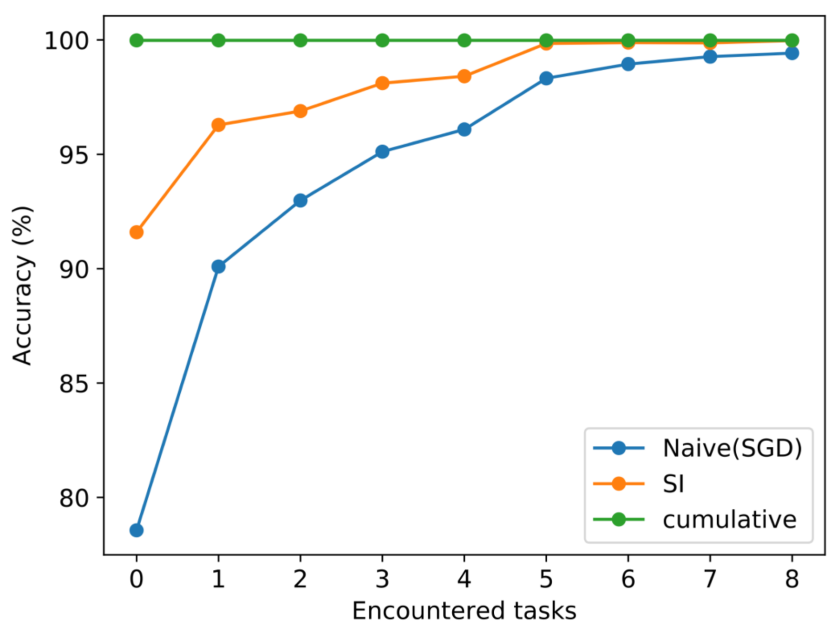
1st round

	Parameter	Round 1	Final Round
SGD	Model	**Resnet-18**	**Resnet-18**
	Batch size	128	128
	Epochs	4	5
	Optimizer	SGD	SGD
	Learning rate	0.001	0.001
Synaptic Intelligence	Regularization factor(SI)	0.2	4
	Epochs	8	8

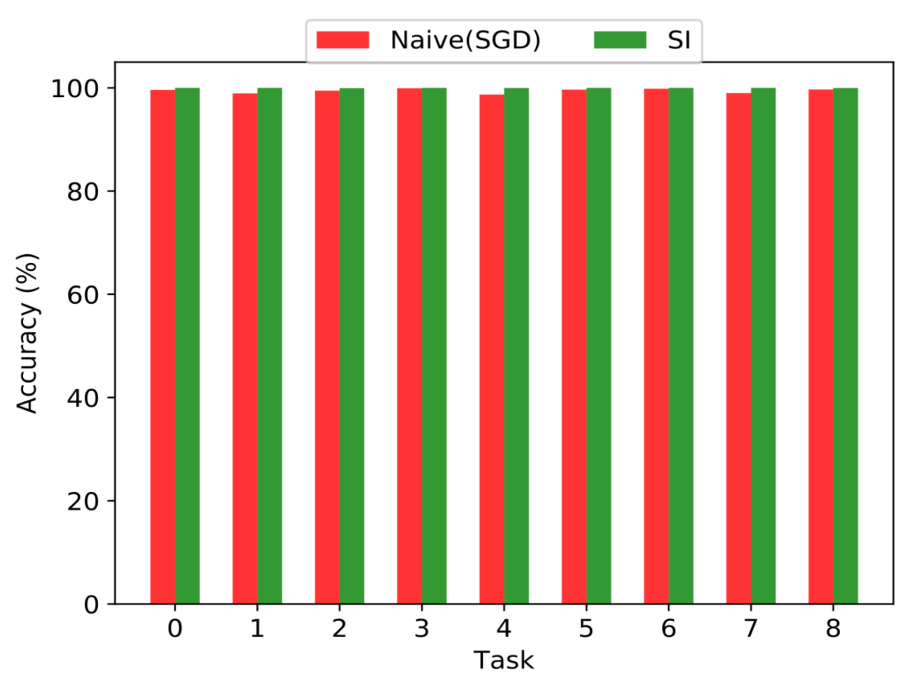


Model Selection

Method	Accuracy
Naive(SGD)	99.42
Cumulative(SGD)	99.98
SGD + SI	99.98



Accuracy vs Encountered tasks

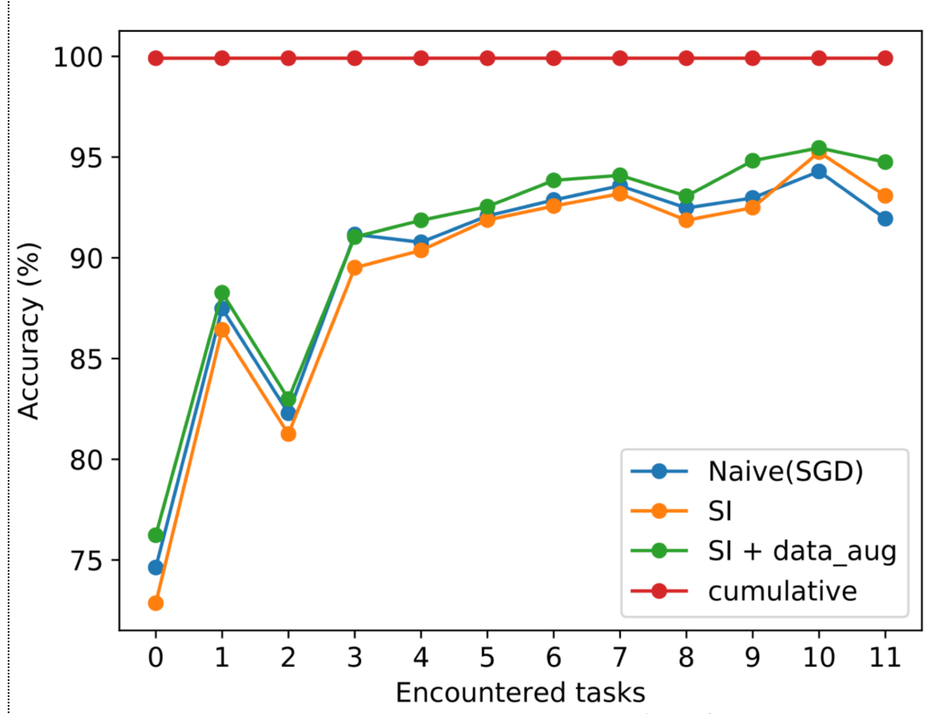


Final Accuracy by task

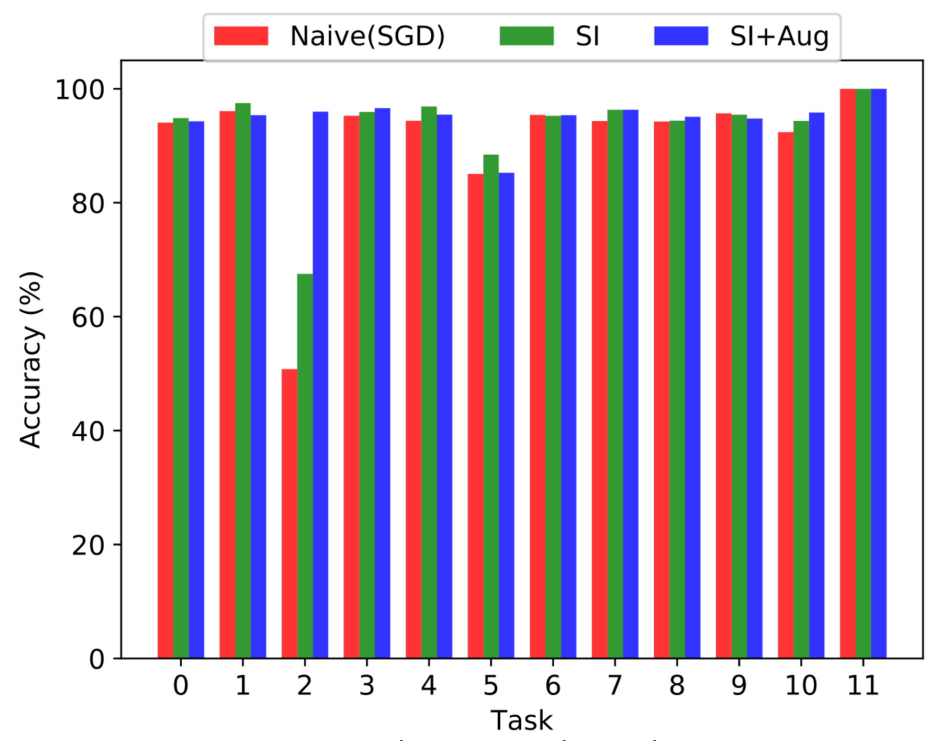
Final Round

	Method	
Final Accuracy(%)	Naive(SGD)	91.94
	Cumulative(SGD)	99.91
	SGD + SI	93.08
	SGD + SI + Aug (Color Jitter)	94.11
	SGD + SI + Aug (Color Jitter + Blur)	**95.04**
	SGD + SI + Aug (Color Jitter + Blur + Affine + Hor. Flip)	91.11
Train Time(min)	SGD + SI	215 min
	SGD + SI + Aug (Color Jitter + Blur)	269 min

TABLE IV: Final round results summary



Accuracy vs Encountered tasks



Final Accuracy by task

6. Conclusion

Synaptic Intelligence based Regularization and ***data augmentation*** increases **generalization** of model and helps to **reduce overfitting** of model to particular environmental conditions