



Class-incremental learning with generative classifiers

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Class-incremental learning

- Main challenge:

→ Learn to distinguish between classes that are not observed together

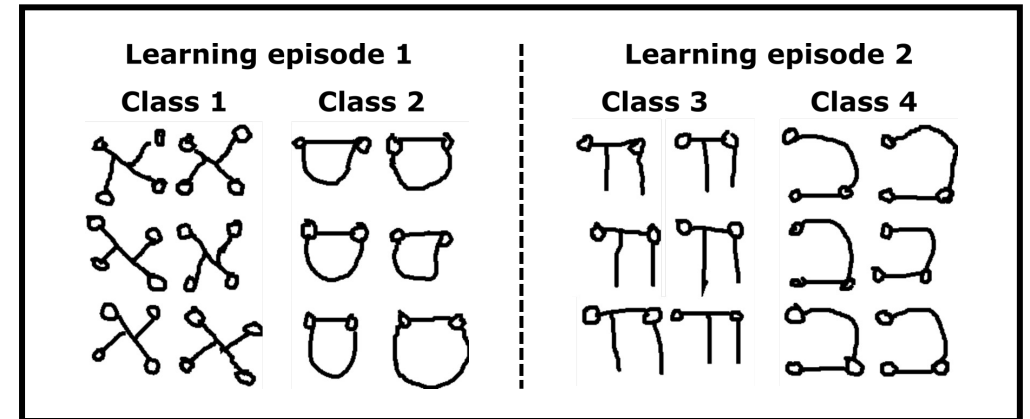
- Existing strategies:

- ~~• Storing previously seen examples~~

- Generative replay (e.g., **DGR**; Shin et al., 2017 *NeurIPS*; **BI-R**; van de Ven et al., 2020 *Nature Communications*)

- Parameter regularization (e.g., **EWC**; Kirckpatrick et al., 2017 *PNAS*; **SI**; Zenke et al., 2017 *ICML*)

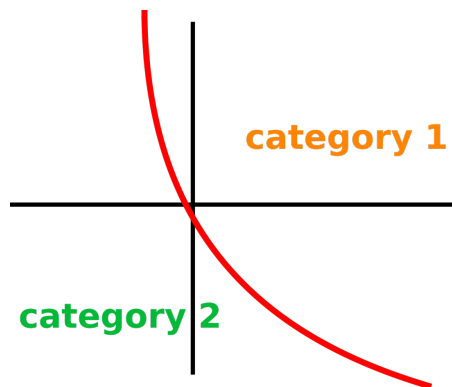
- Bias-correction (e.g., **CWR**; Lomonaco & Maltoni, 2017 *CoRL*; **AR1** Maltoni & Lomonaco, 2019 *Neural Networks*; “**Labels trick**” Zeno et al., 2019 *arXiv*)



Proposed strategy: generative classification

Discriminative classifiers

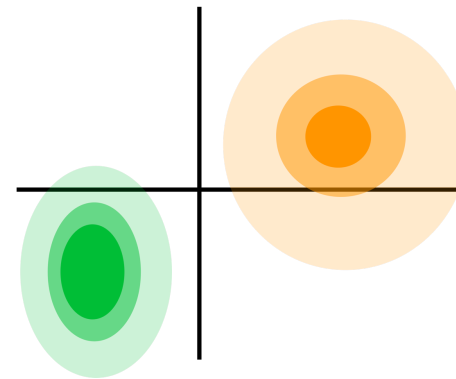
- Directly learn $p(y|\mathbf{x})$, or $\operatorname{argmax}_y p(y|\mathbf{x})$.



- Learn rules / shortcuts / features to distinguish between the classes to be learned
- Comparison between classes is during *training*

Generative classifiers

- Learn $p(\mathbf{x}, y)$, factorized as $p(\mathbf{x}|y)p(y)$, and classify using Bayes' rule



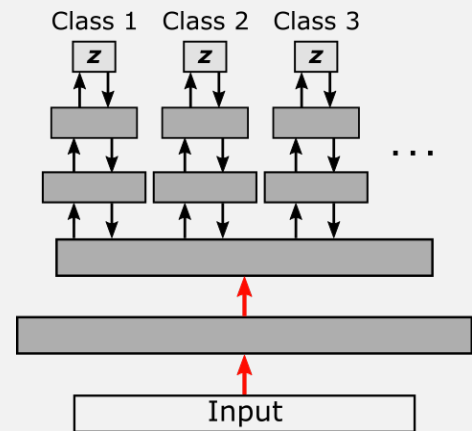
- Learn a model / template / representation for each class to be learned
- Comparison between classes is during *inference*

Generative classification ***rephrases a class-incremental problem as a task-incremental problem***, whereby each 'task' is to learn a class-conditional generative model.

Naïve implementation for proof-of-principle

- Separate VAE model for each class
- If a pretrained network is available, the VAE models are trained on the latent features
- Class-conditional likelihoods are estimated using importance sampling
- The *total* number of parameters is similar to that of generative replay

Schematic



Making a classification decision

- (1) Estimate class-conditional likelihoods

$$p(\mathbf{x}_{\text{test}}|y = 1) \quad p(\mathbf{x}_{\text{test}}|y = 2) \quad p(\mathbf{x}_{\text{test}}|y = 3) \quad \dots$$

- (2) Classify using Bayes' rule

$$\hat{y}(\mathbf{x}_{\text{test}}) = \underset{i}{\operatorname{argmax}} p(\mathbf{x}_{\text{test}}|y = i)$$

Results

Strategy	Method	MNIST	CIFAR-10	CIFAR-100	CORe50
<i>Baselines</i>	<i>None</i>	19.92 (± 0.02)	18.74 (± 0.29)	7.96 (± 0.11)	18.65 (± 0.26)
	<i>Joint</i>	98.23 (± 0.04)	82.07 (± 0.15)	54.08 (± 0.27)	71.85 (± 0.30)
Generative Replay	DGR	91.30 (± 0.60)	17.21 (± 1.88)	9.22 (± 0.24)	-
	BI-R	-	-	21.51 (± 0.25)	60.40 (± 1.04)
	BI-R + SI	-	-	34.38 (± 0.21)	62.68 (± 0.72)
Regularization	EWC	19.95 (± 0.05)	18.63 (± 0.29)	8.47 (± 0.09)	18.56 (± 0.31)
	SI	19.95 (± 0.11)	18.14 (± 0.36)	8.43 (± 0.08)	18.69 (± 0.26)
Bias-correction	CWR	32.48 (± 2.64)	18.37 (± 1.61)	21.90 (± 0.68)	40.28 (± 1.13)
	CWR+	37.20 (± 3.11)	22.32 (± 1.08)	9.34 (± 0.25)	40.12 (± 1.06)
	AR1	48.84 (± 2.55)	24.44 (± 1.08)	20.62 (± 0.45)	45.27 (± 1.02)
	Labels Trick	32.46 (± 1.95)	18.43 (± 1.31)	23.68 (± 0.26)	42.59 (± 1.03)
Other	SLDA	87.30 (± 0.02)	38.35 (± 0.03)	44.49 (± 0.00)	70.80 (± 0.00)
Generative Classifier		93.79 (± 0.08)	56.03 (± 0.04)	49.55 (± 0.06)	70.81 (± 0.11)

Results: generative replay vs. generative classification

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	BI-R + SI	-	-	34.38 (± 0.21)	62.68 (± 0.72)
	EWC	10.05 (± 0.05)	18.63 (± 0.20)	8.47 (± 0.00)	18.56 (± 0.31)
Other	SLDA	87.30 (± 0.02)	38.35 (± 0.03)	44.49 (± 0.00)	70.80 (± 0.00)
Generative Classifier		93.79 (± 0.08)	56.03 (± 0.04)	49.55 (± 0.06)	70.81 (± 0.11)

How to best use a learned generative model?

Generate samples to train a discriminative classifier?

Generative classification?

Take-home message

- Generative classification is a promising strategy for class-incremental learning and a fruitful direction for future research

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