

#### Deep Online Storage-Free Learning on Unordered Image Streams

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# Deep Online Storage-Free Learning on Unordered Image Streams

## BACKGROUND

Deep learning on data streams vs static learning, application for the classification task

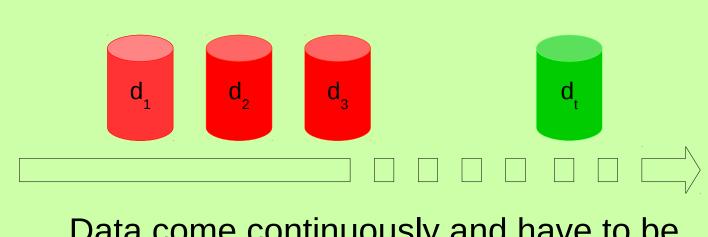
Static data

The whole dataset is stored on the disc and is available at any moment.

#### Deep learning on static dataset

- 1) Dataset is of a limited size and exact training time per epoch can always be estimate.
- 2) Sizes of data classes are usually similar or can be equalized before training
- 3) The whole dataset is available for learning and retraining at any moment
- 4) All the data classes are available at every training epoch. Moreover, training Is based on gradient-based methods, usually need multiple training epochs
- 5) Number of classes together with labels for each data sample are provided before training.

### Stream data

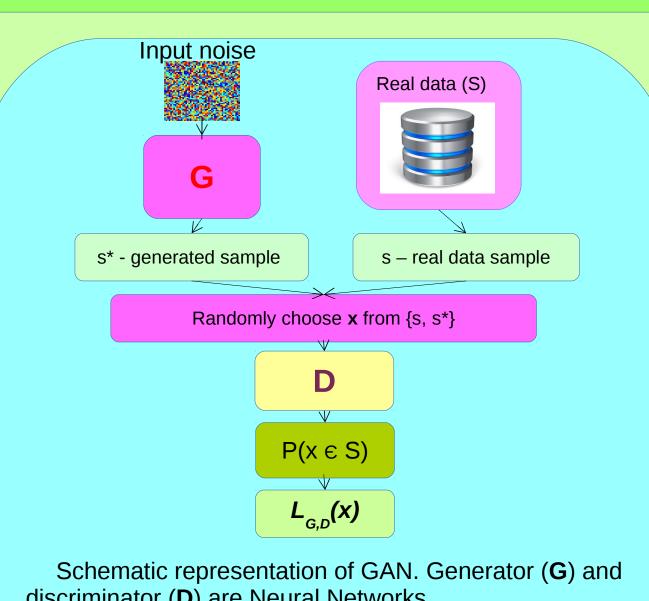


Data come continuously and have to be processed in real time.

#### Deep learning on data streams

- 1) Data comes with high speed → Need **real** time information extraction and learning.
- 2) Classes don't have to be equal → Want to learn well on classes of different sizes.
- 3) Streams are potentially of a very big (infinite) size → Want to avoid storing historical data.
- 4) At some point several data classes can never appear again in the stream → Need to avoid catastrophic forgetting of already learned information.
- 5) Data classes, never seen by the learning system before, can appear → Need a model, able to adapt to new classes

# Generative Adversarial Networks (GAN) [1]



discriminator (D) are Neural Networks. **G** is taught to produce samples similar to the real data and **D** is simultaneously trained to distinguish generated

samples from the real ones.

Original Images Generated Images 040296124 58275217 46960033 LSUN<sup>(b)</sup> Examples of images, used for training (left)

and samples, generated with GANs (right)

Minimax game between G and D is based on loss function:

 $min_{G} max_{D} L_{G,D}(\mathbf{x}) = E_{x \sim p_{s}(\mathbf{x})}[\log D(\mathbf{x})] + E_{s * \sim p_{s*}(s*)}[\log (1 - D(G(s*)))]$ 

### Deep Convolutional GANs [2] – difference from classic GANs:

- All pooling layers are replaced by strided convolutions, which allows the network learn its own down-sampling
- Batch normalization[3] is used to avoid poor initialization problems.
- No fully-connected hidden layers
- Better suited for image datasets

(a) Dataset is available at http://yann.lecun.com/exdb/mnist/ (b) Dataset is available at http://lsun.cs.princeton.edu/2016/

1) Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014.

2) Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." arXiv preprint arXiv:1511.06434 (2015).

## Ideas in development and perspectives

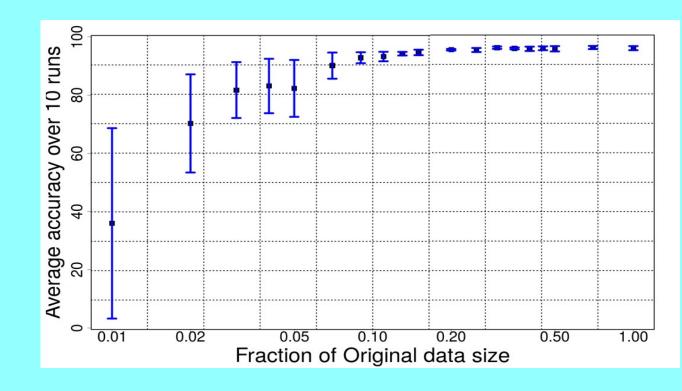
- Move forward more efficient learning → Better performance with less training examples (one-shot learning, non-gradient optimization methods, ...)
- Define and implement sub-space constrains when learning new data classes to avoid catastrophic forgetting without reusing historical information at all.
- Study the "separability" of Neural Networks activations, depending on data type/class, to introduce activation scheduling inside networks → more efficient learning with less forgetting

# Learning classification models on streams with no storage using GANs

#### **Batch** learning on generated data (MNIST dataset)

**Goal**: To check the ability of generative models to produce data that represent well the initial dataset before passing to the online scenario Method:

- Train one generator per data class
  - Use generators to recreate synthetic dataset of the size, proportional to the initial one
- Train batch classifier on generated dataset
- Test obtained classifier on the original validation set



#### **Results:**

- We get to stable accuracy with the size of generated set of 20% of the initial training set
- Lose >4% in accuracy comparing to the original data usage – the price to pay for not storing the data
- Using more advanced generative models should reduce the loss

#### Adaptive learning on incremental data stream

#### Goal:

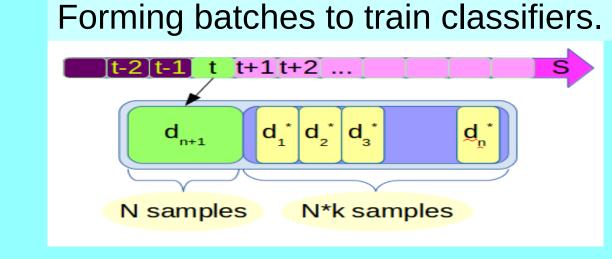
\* k=1 → k=1.5

-k=7

- Use generative models in classification scenario on data stream with data arriving incrementally class-by-class to remove the necessity of storing historical data while not introducing forgetting
- Check the influence of the amount of generated data on classification accuracy

Schematic representation of proposed solution:

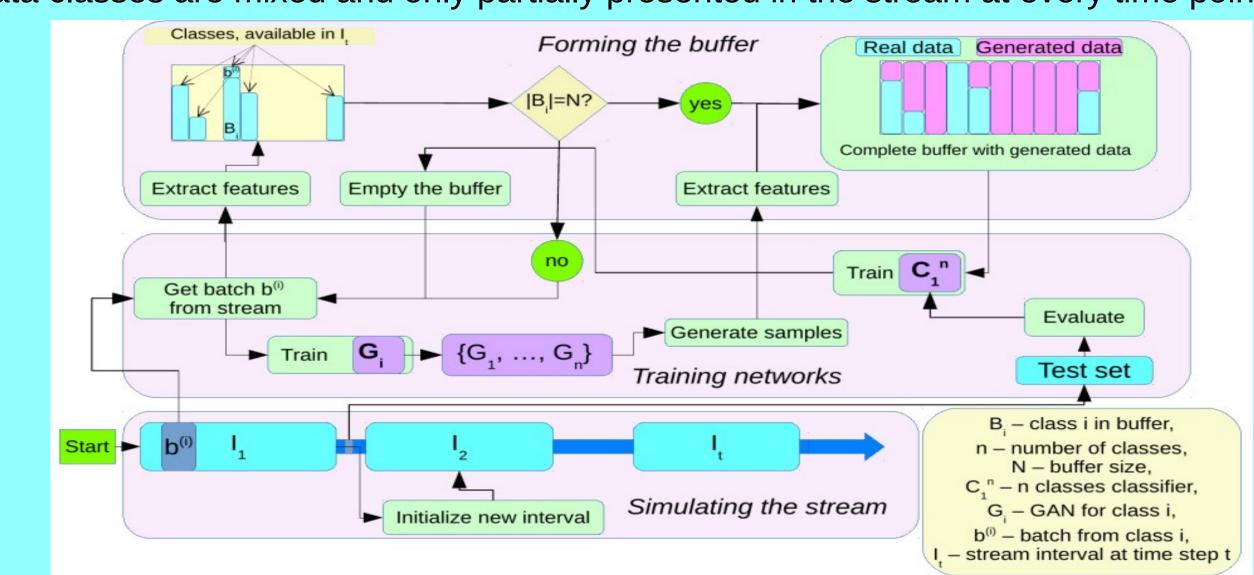
Number of learned classes

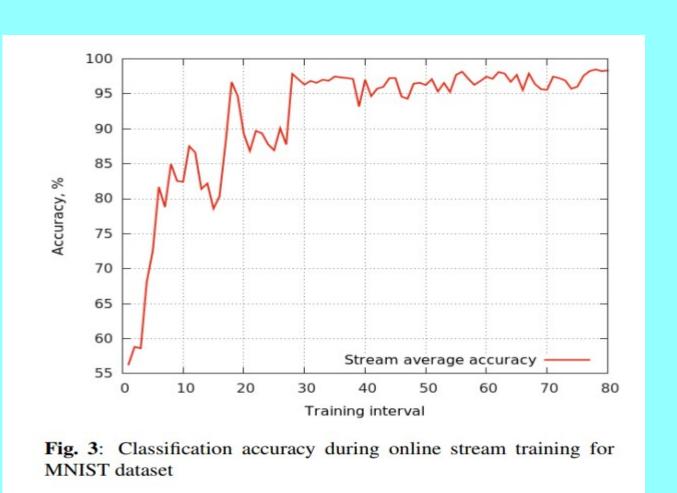


- Small values of **k** provoke forgetting, previously learned classes get crushed
- ~94% classification accuracy with big enough **k** in completely online settings (99.6% in batch mode with the same net architecture)
- Very big  $\mathbf{k} = \mathbf{a}$  lot of data to generate, can become a problem for the datasets with 100+ classes

#### Online learning in realistic stream scenario on complex dataset (LSUN)

Data classes are mixed and only partially presented in the stream at every time point





Mean - std • Training interval

Fig. 4: Classification accuracy during online stream training for LSUN dataset. Each point on the graph corresponds to the average value over 80 training intervals