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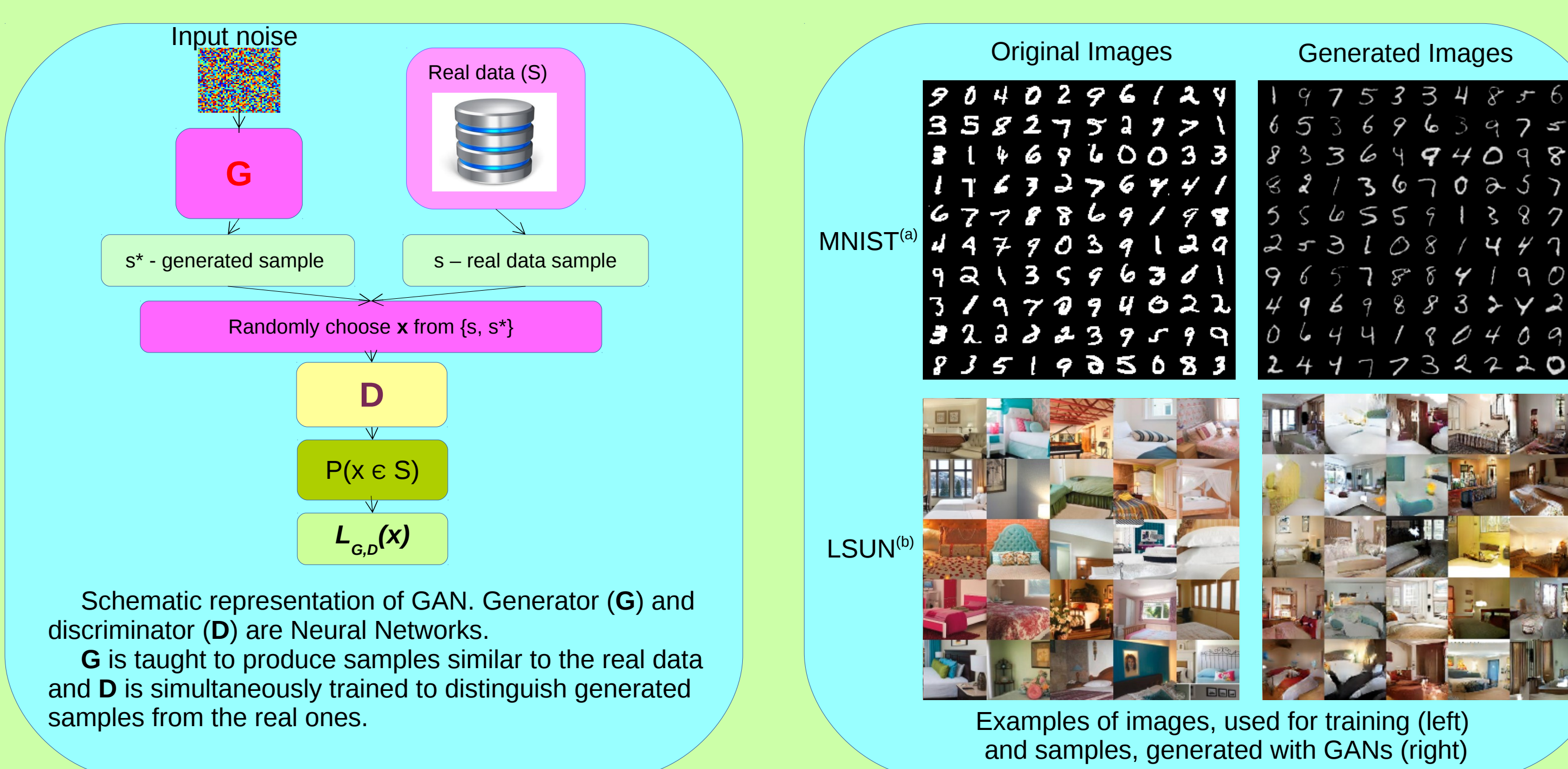
# Deep Online Storage-Free Learning on Unordered Image Streams

## BACKGROUND

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

Static data	Stream data
<p>The whole dataset is stored on the disc and is available at any moment.</p>	<p>Data come continuously and have to be processed in real time.</p>
Deep learning on static dataset	Deep learning on data streams
<ol style="list-style-type: none"> <li>1) Dataset is of a limited size and exact training time per epoch can always be estimate.</li> <li>2) Sizes of data classes are usually similar or can be equalized before training</li> <li>3) The whole dataset is available for learning and retraining at any moment</li> <li>4) All the data classes are available at every training epoch. Moreover, training is based on gradient-based methods, usually need multiple training epochs</li> <li>5) Number of classes together with labels for each data sample are provided before training.</li> </ol>	<ol style="list-style-type: none"> <li>1) Data comes with high speed → Need <b>real time information extraction and learning</b>.</li> <li>2) Classes don't have to be equal → Want to <b>learn well on classes of different sizes</b>.</li> <li>3) Streams are potentially of a very big (infinite) size → Want to <b>avoid storing historical data</b>.</li> <li>4) At some point several data classes can never appear again in the stream → Need to <b>avoid catastrophic forgetting</b> of already learned information.</li> <li>5) Data classes, never seen by the learning system before, can appear → Need a model, able to <b>adapt to new classes</b></li> </ol>

## Generative Adversarial Networks (GAN) [1]



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

$$\min_G \max_D L_{G,D}(x) = E_{x \sim p_s(x)} [\log D(x)] + E_{s^* \sim p_{s^*}(s^*)} [\log(1 - D(G(s^*)))]$$

### 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

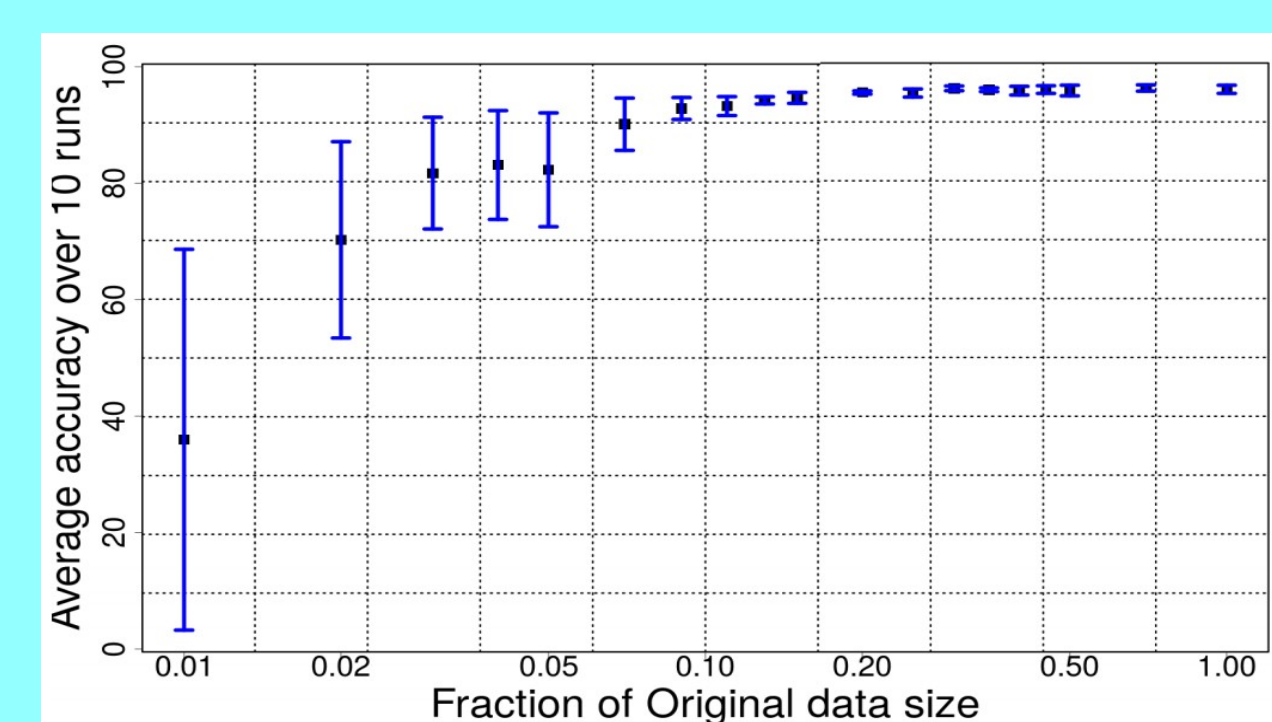
- Move forward more efficient learning → Better performance with less training examples (one-shot learning, non-gradient optimization methods, ...)
- Define and implement sub-space constrains when learning new data classes to avoid catastrophic forgetting without reusing historical information at all.
- 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:

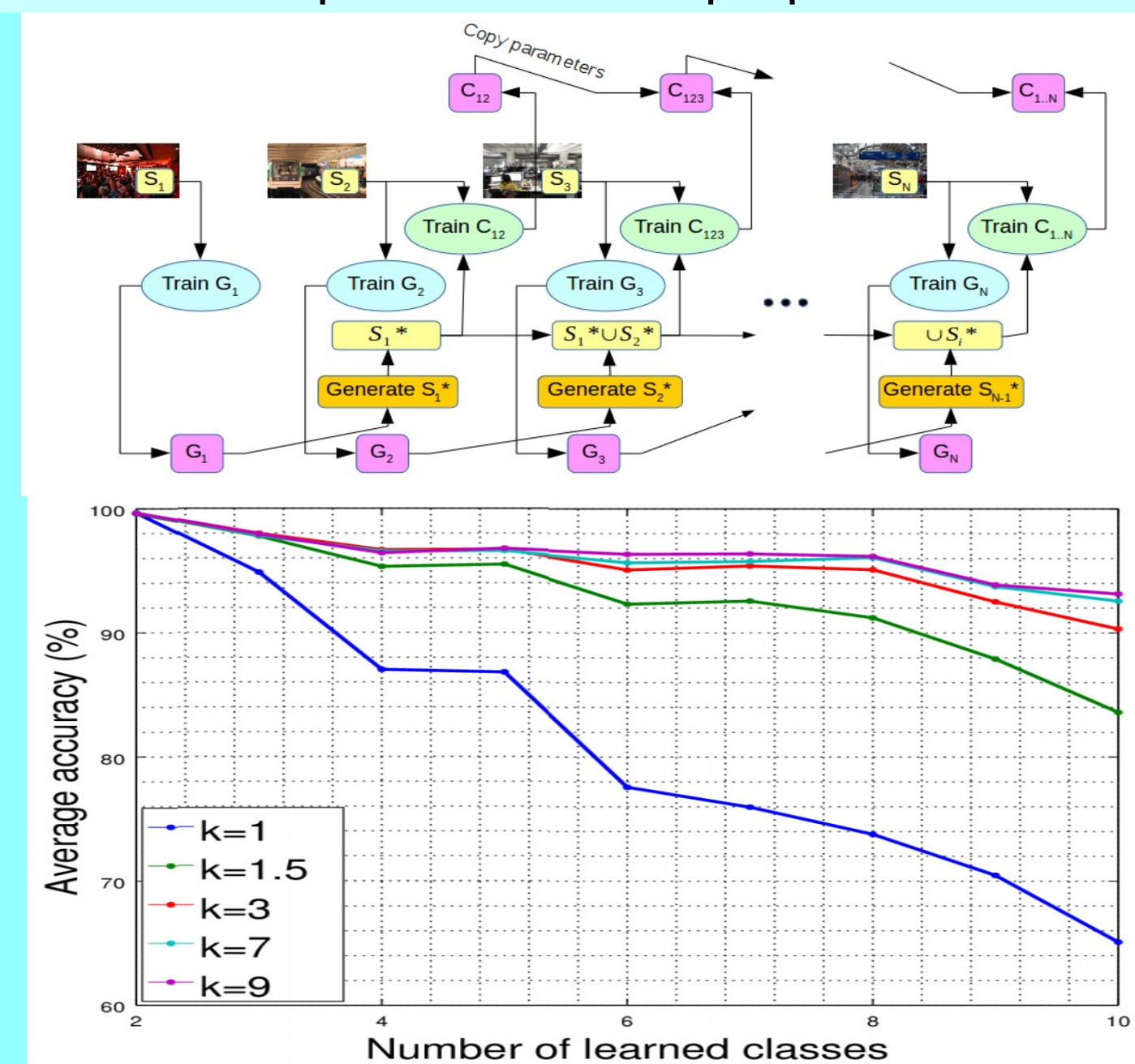
- We get to stable accuracy with the size of generated set of 20% of the initial training set
- Lose >4% in accuracy comparing to the original data usage – the price to pay for not storing the data
- Using more advanced generative models should reduce the loss

### Adaptive learning on incremental data stream

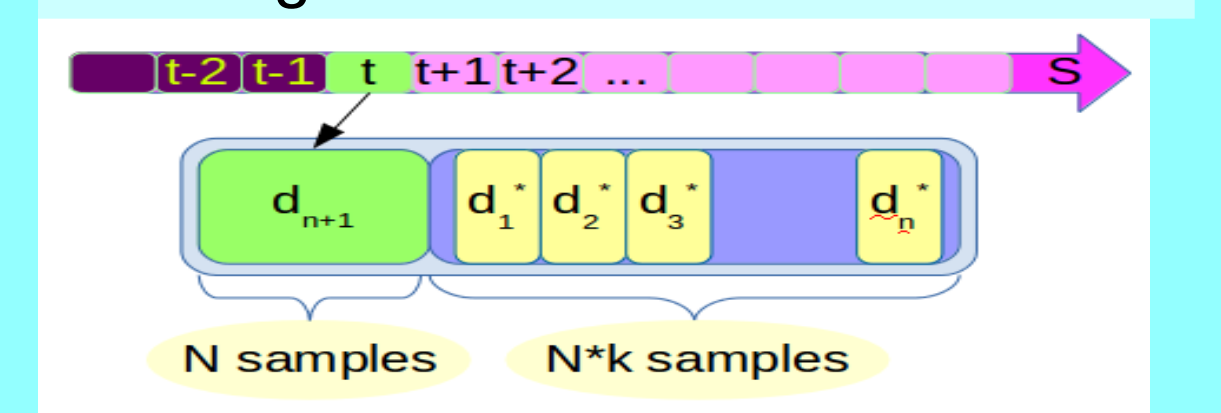
**Goal:**

- 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:



Forming batches to train classifiers.



- 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 k = 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

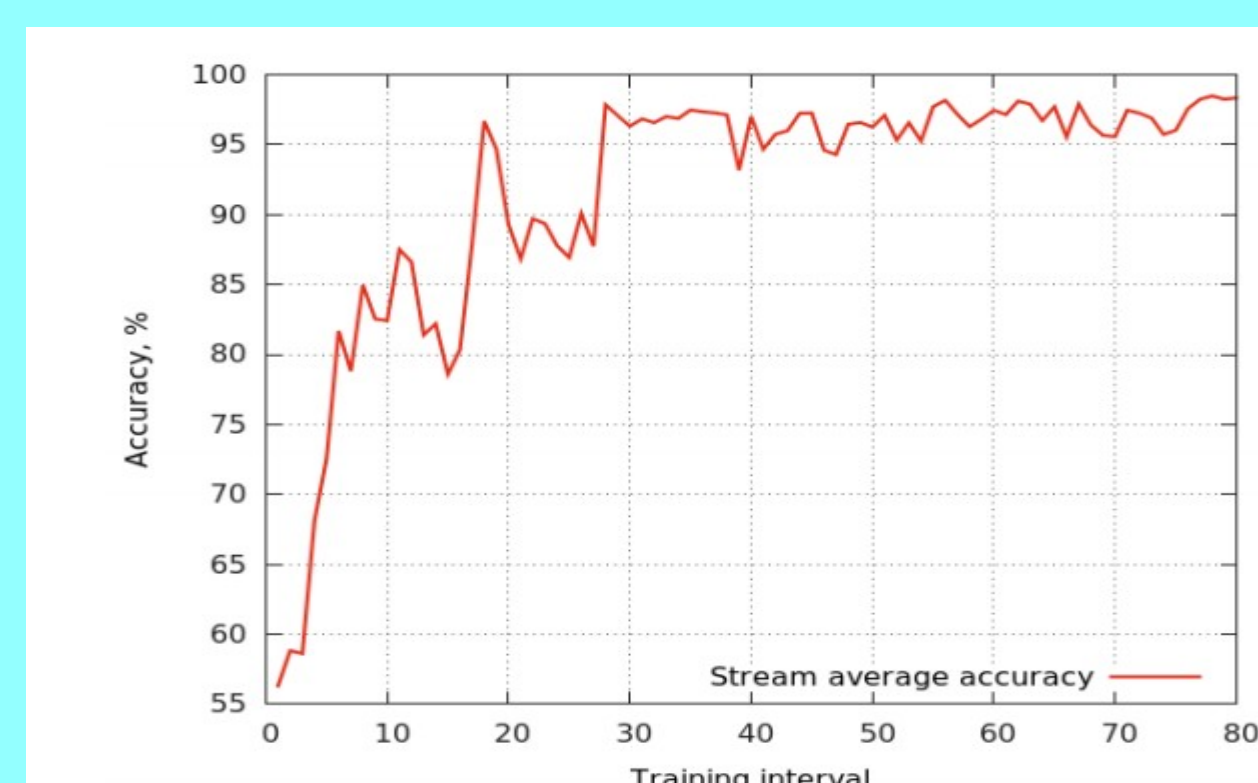
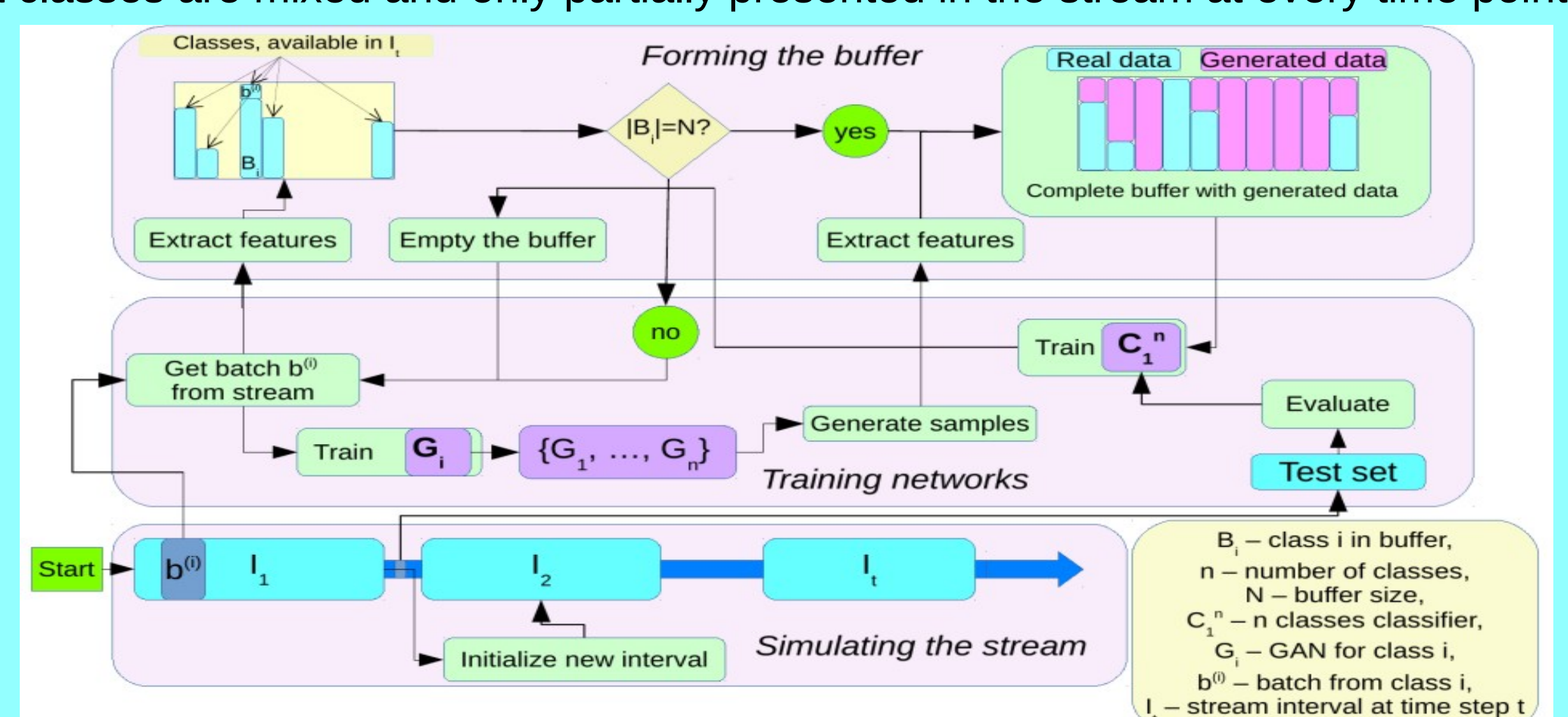


Fig. 3: Classification accuracy during online stream training for MNIST dataset

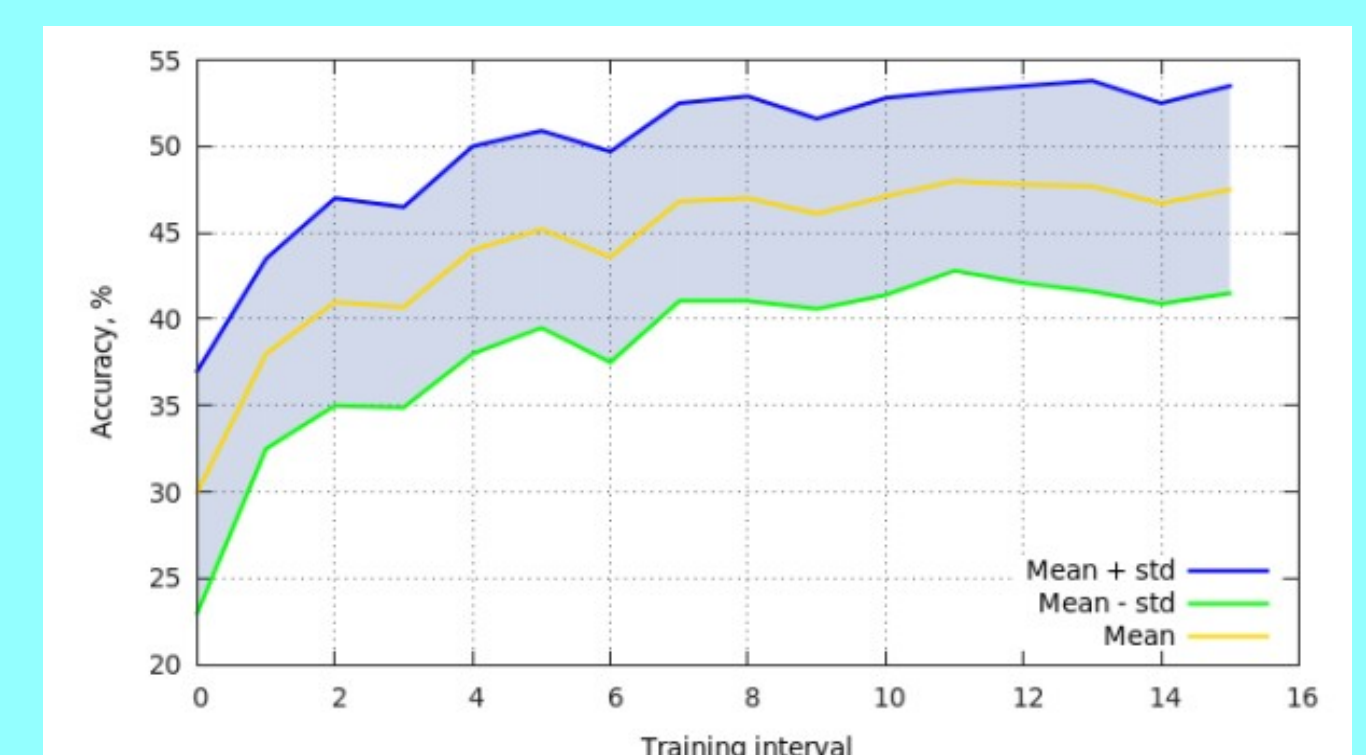


Fig. 4: Classification accuracy during online stream training for LSUN dataset. Each point on the graph corresponds to the average value over 80 training intervals