Context Encoders

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Contents

Abstract

Visual feature learning algorithm based on context based pixel prediction (surrounding based).

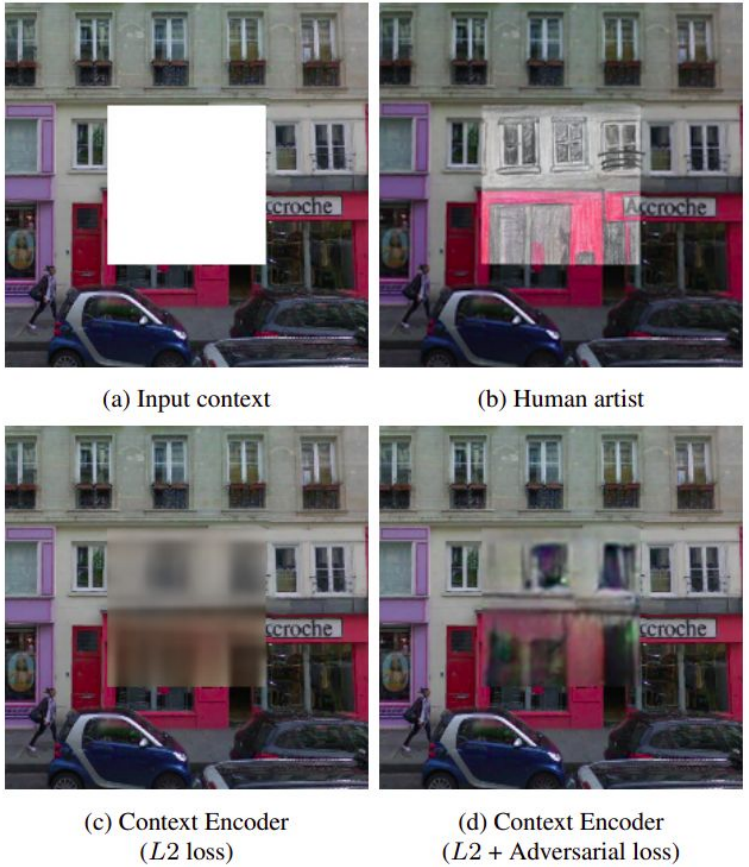
Two main parts

- The content of the image should be extracted.
- Plausible hypothesis should be provided for the missing parts.

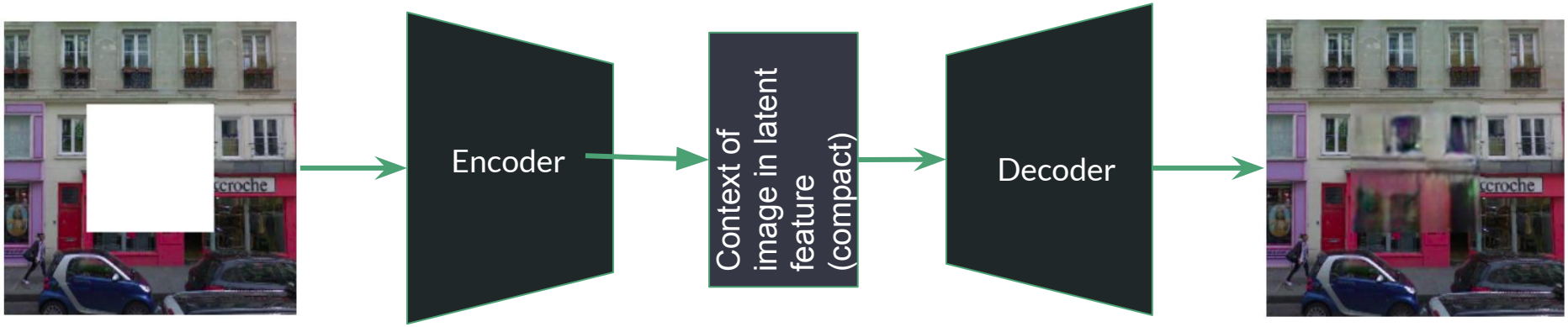
Better results are obtained when a reconstruction loss plus an adversarial loss is used over standard pixel wise reconstruction loss.

Introduction

- Exploring if state-of-the-art computer vision algorithms can make a sense of the structure as humans do.
- In this paper they learn and predict the structure using convolutional neural networks.(shown below)



Model



The feature we get is likely to be just the compressed version of the image without learning any meaningful representation.

Denoising autoencoders address this by corrupting the image (this can be used when there isn't much semantic information)

Here we need to fill large missing parts of image, we require deeper semantic understanding.

This task, however, is inherently multi-modal as there are multiple ways to fill the missing region while also maintaining coherence with the given context.

They decouple this burden in the loss function by jointly training our context encoders to minimize both a reconstruction loss and an adversarial loss.

Encoder - Context of the image patch is extracted and nearest neighbour contexts produces similar patches.

Fine tune - encoder to variety of image understanding tasks to validate the quality of the feature

Decoder - parametric in painting , context encoder (non - parametric painting method).

Related work

Unsupervised learning - autoencoders , denoising autoencoders

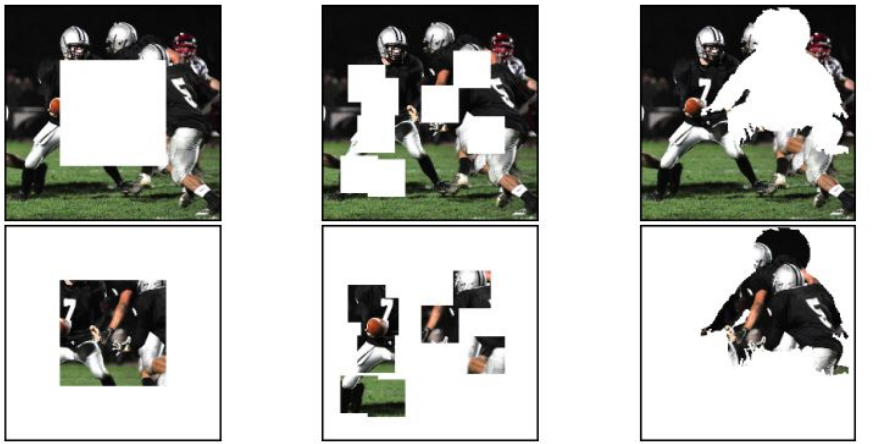
.Weakly-supervised and self-supervised learning - supervision from temporal information contained in videos, in this paper spatial context is exploited as a source of free and plentiful supervisory signal.

Image Generation - GANs, in this paper, context encoders using an adversary jointly with reconstruction loss for generating inpainting results.

Inpainting and hole-filling- Can’t be filled with classical inpainting as missing region is too large, graphics scene completion fails to fill arbitrary holes, this method is able to inpaint semantically meaningful content in a parametric fashion, as well as provide a better feature for nearest neighbor-based inpainting methods.

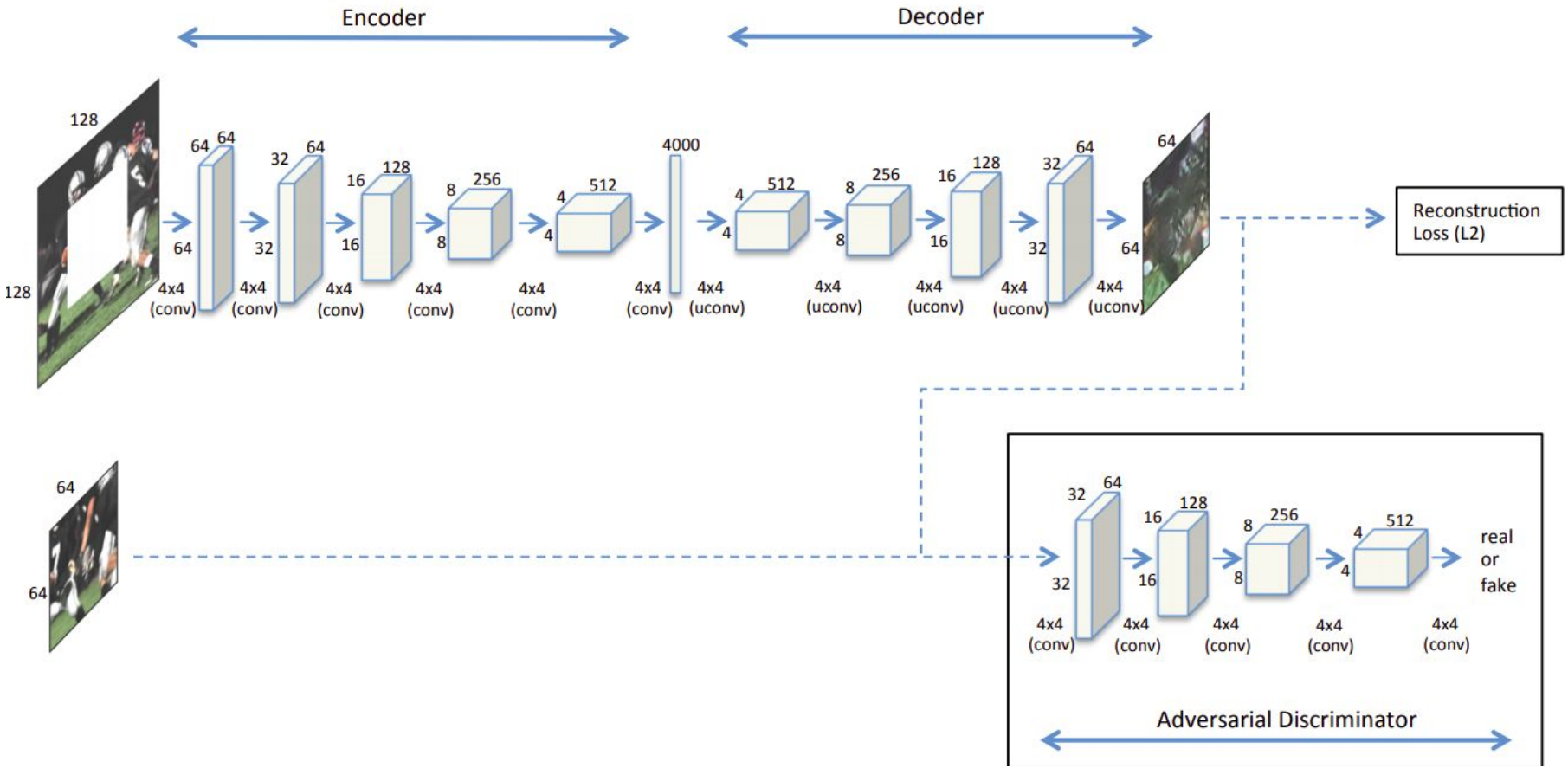
Region Masks

The input to a context encoder is an image with one or more of its regions “dropped out”; i.e., set to zero, assuming zero-centered inputs. The removed regions could be of any shape, we present three different strategies here:

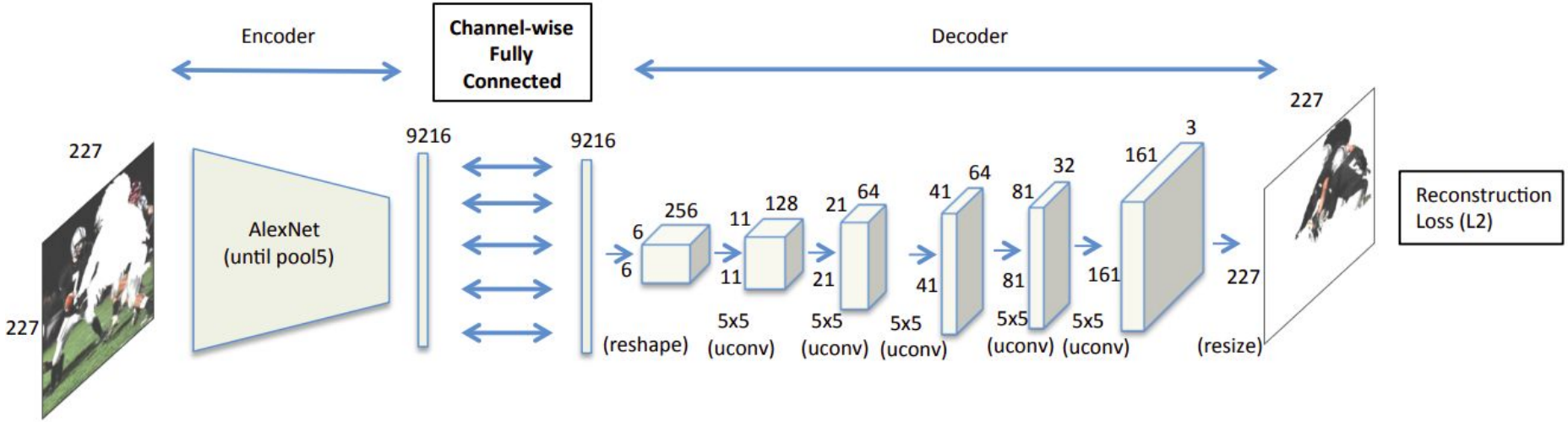


(a) Central region (b) Random block (c) Random region

Current network



Next phase



(b) Context encoder trained with reconstruction loss for feature learning by filling in *arbitrary region dropouts* in the input.

Context encoders for image generation

Encoder-decoder pipeline

- Simple encoder-decoder pipeline.
- Encoder takes an input image with missing regions and produces a latent feature representation of that image
- Decoder takes this feature representation and produces the missing image content.
- Encoder and decoder should be connected with a channel wise fully connected layer, so decoder can reason with the whole image content.

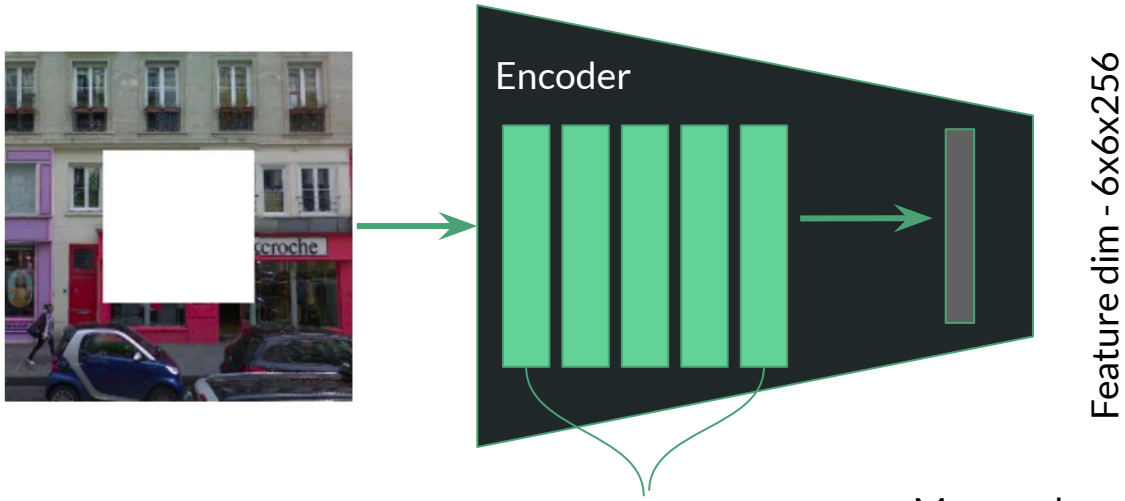
Pool-free encoders - They experimented with replacing all pooling layers with convolutions of the same kernel size and stride.

The overall stride of the network remains the same, but it results in finer inpainting.

Intuitively, there is no reason to use pooling for reconstruction based networks.

Original AlexNet architecture (with pooling) for all feature learning results is used.

Encoder



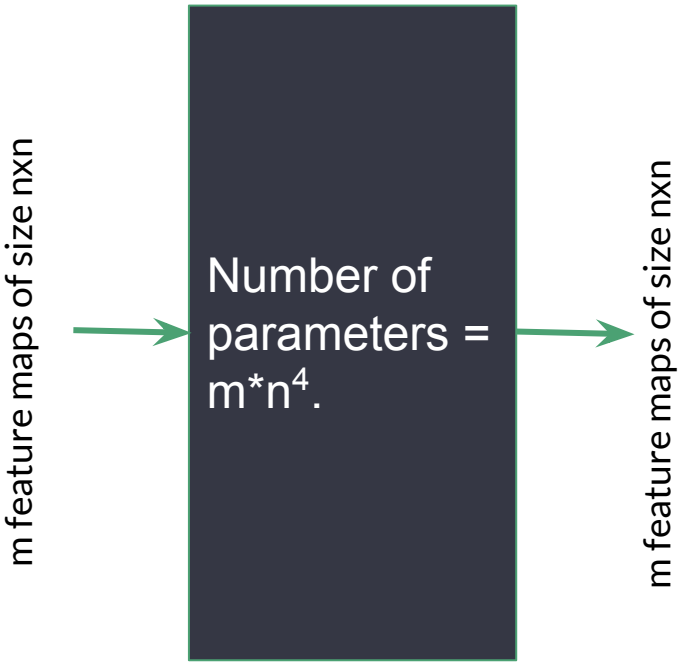
If only convolutional layers are used then all feature maps will be connected together but no connections within a specific map.

To handle this we use fully connected layer.

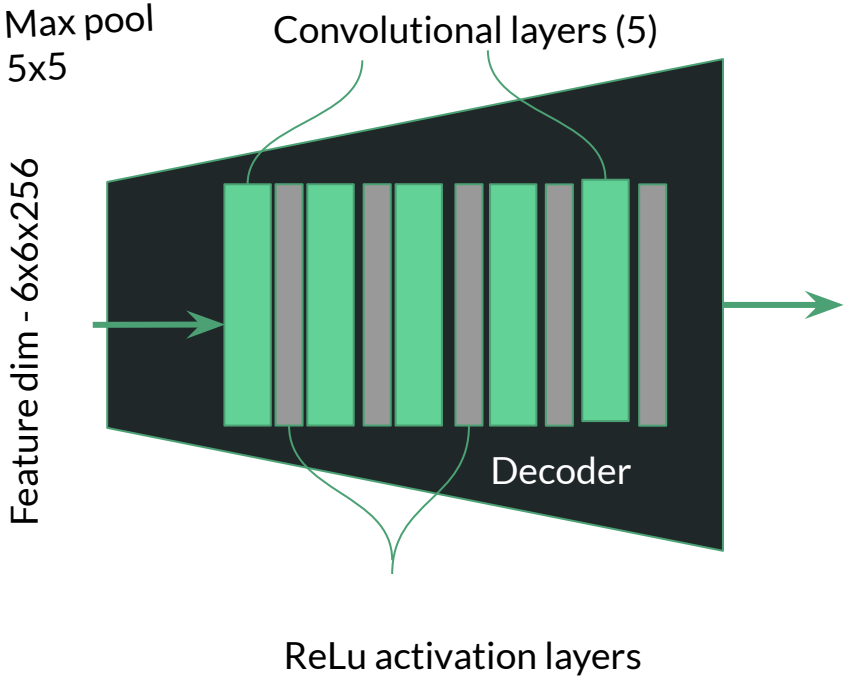
Channel-wise fully-connected layer

This layer is essentially a fully-connected layer with groups, intended to propagate information within activations of each feature map.

However, unlike a fully-connected layer, it has no parameters connecting different feature maps and only propagates information within feature maps.



Decoder



It can be understood as upsampling followed by convolution, or convolution with fractional stride.

The intuition behind this is straightforward non-linear weighted upsampling of the feature produced by the encoder until we roughly reach the original target size.

Loss Function

Loss function

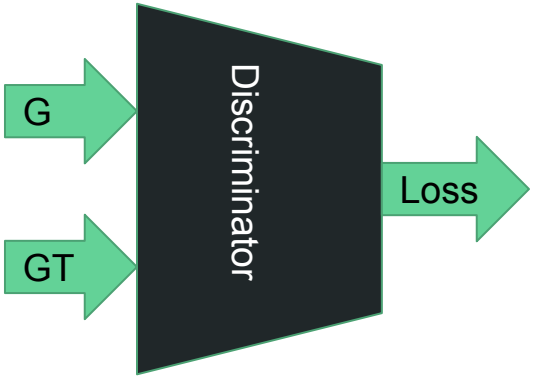
Reconstruction Loss - Normalised L2 distance , it encourages the decoder to produce a rough outline of the predicted object, but does not indicate detail.

$$\mathcal{L}_{rec}(x) = \|\hat{M} \odot (x - F((1 - \hat{M}) \odot x))\|_2^2,$$

Adversarial Loss - Based on GANs To learn a generative model G of a data distribution and learn an adversarial discriminative model D to provide loss gradients to the generative model.

G and D are parametric functions (e.g., deep networks) where G : Z ➔ X maps samples from noise distribution Z to data distribution X .

The learning procedure is a two-player game where an adversarial discriminator D takes in both the prediction of G and ground truth samples, and tries to distinguish them, while G tries to confuse D by producing samples that appear as “real” as possible. (G - Generated image, GT - Ground Truth).



The objective for discriminator is logistic likelihood indicating whether the input is real sample or predicted one:

$$\min_G \max_D \quad \mathbb{E}_{x \in \mathcal{X}}[\log(D(x))] + \mathbb{E}_{z \in \mathcal{Z}}[\log(1 - D(G(z)))]$$

To customize GANs for this task, one could condition on the given context information; i.e., the mask Mˆ x.

However, conditional GANs don't train easily for context prediction task as the adversarial discriminator D easily exploits the perceptual discontinuity in generated regions and the original context to easily classify predicted versus real samples.

We thus use an alternate formulation, by conditioning only the generator (not the discriminator) on context. Modified adversarial loss is:

$$\mathcal{L}_{adv} = \max_{D} \quad \mathbb{E}_{x \in \mathcal{X}}[\log(D(x)) + \log(1 - D(F((1 - \hat{M}) \odot x)))],$$

where, in practice, both F and D are optimized jointly using alternating SGD. Note that this objective encourages entire output of the context encoder to look realistic, not just the missing regions as before

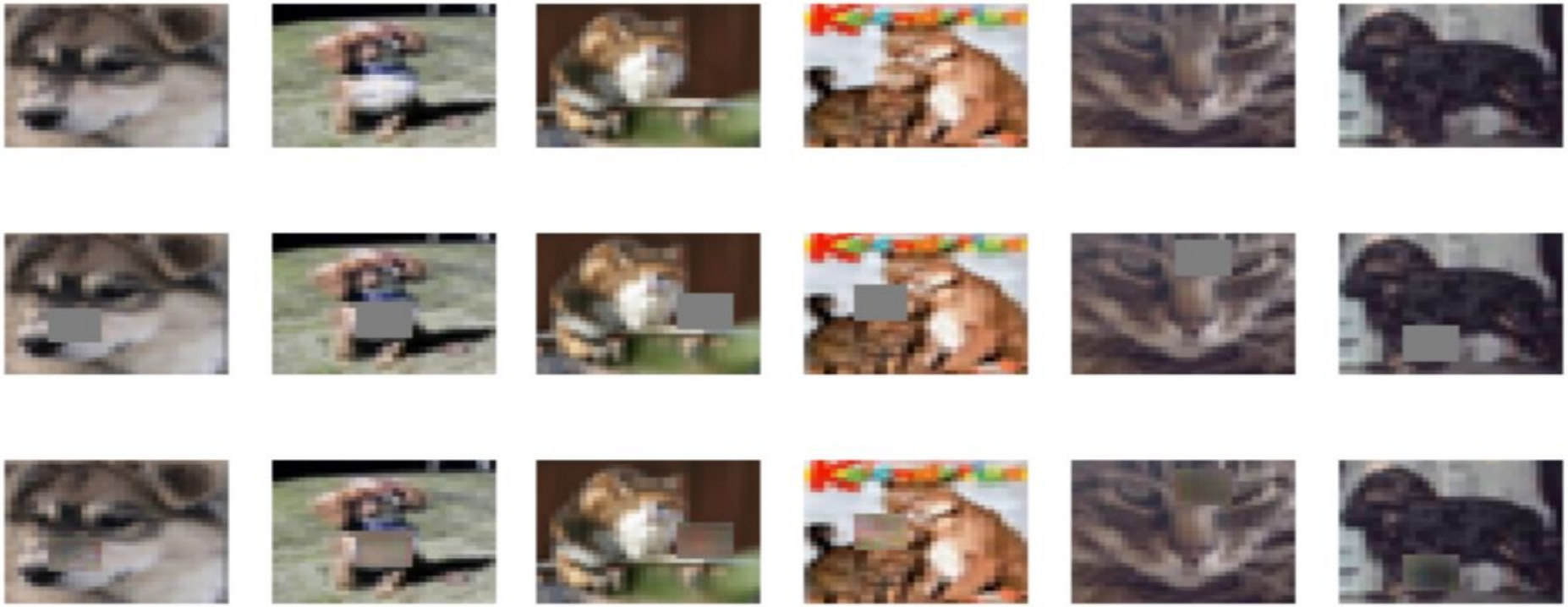
Joint loss

We define the overall loss function as

$$\mathcal{L} = \lambda_{rec}\mathcal{L}_{rec} + \lambda_{adv}\mathcal{L}_{adv}.$$

Results

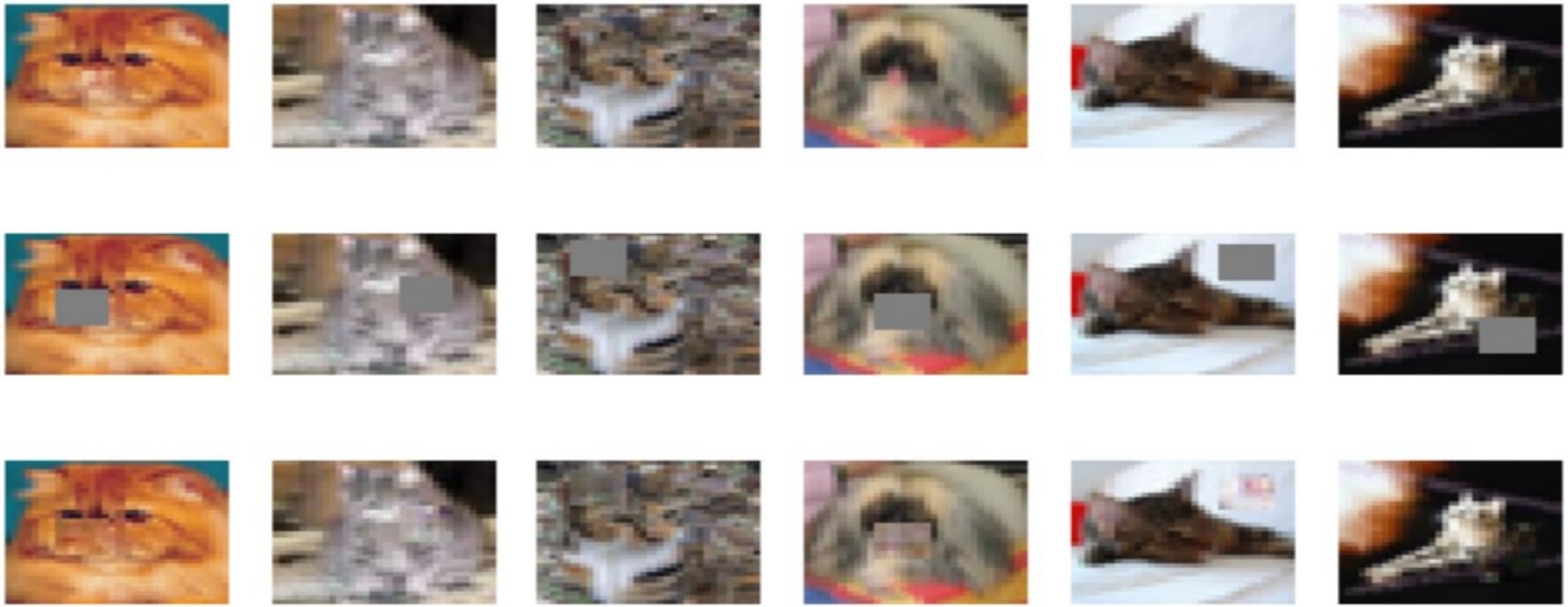
Iteration :200



Iteration :800

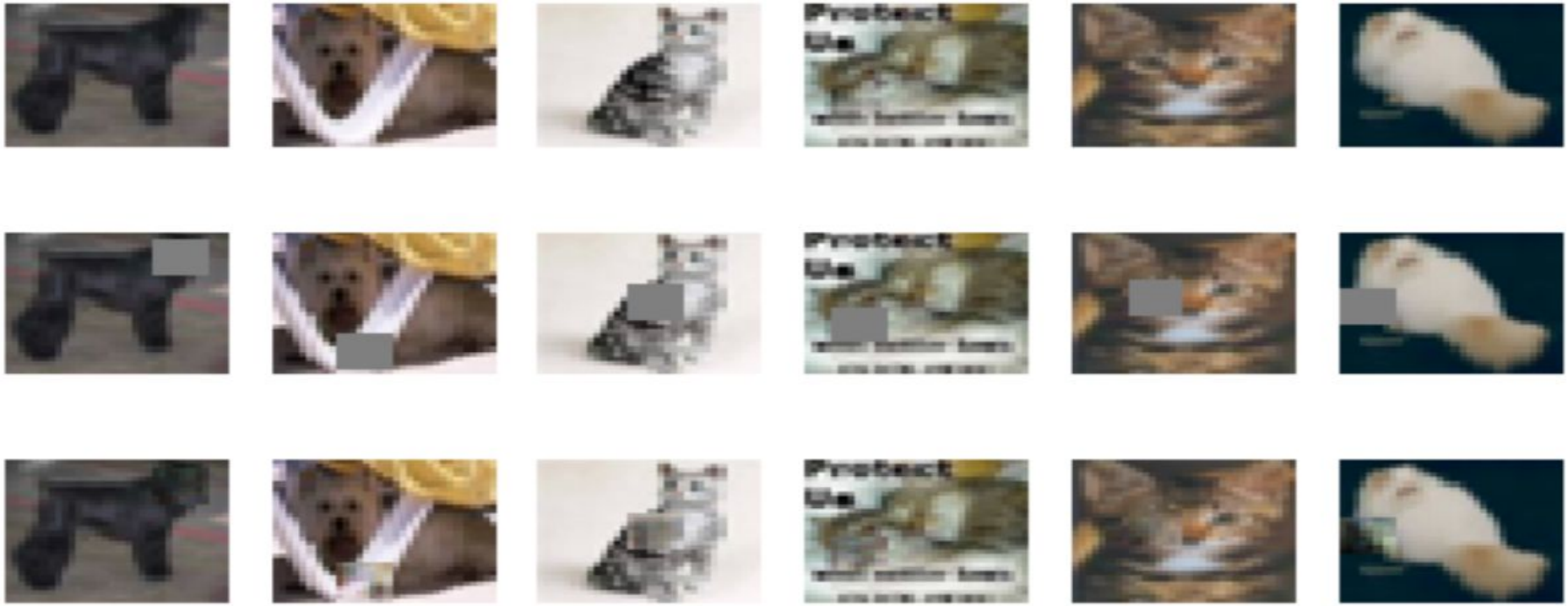
Iteration :1700

Iteration :5300

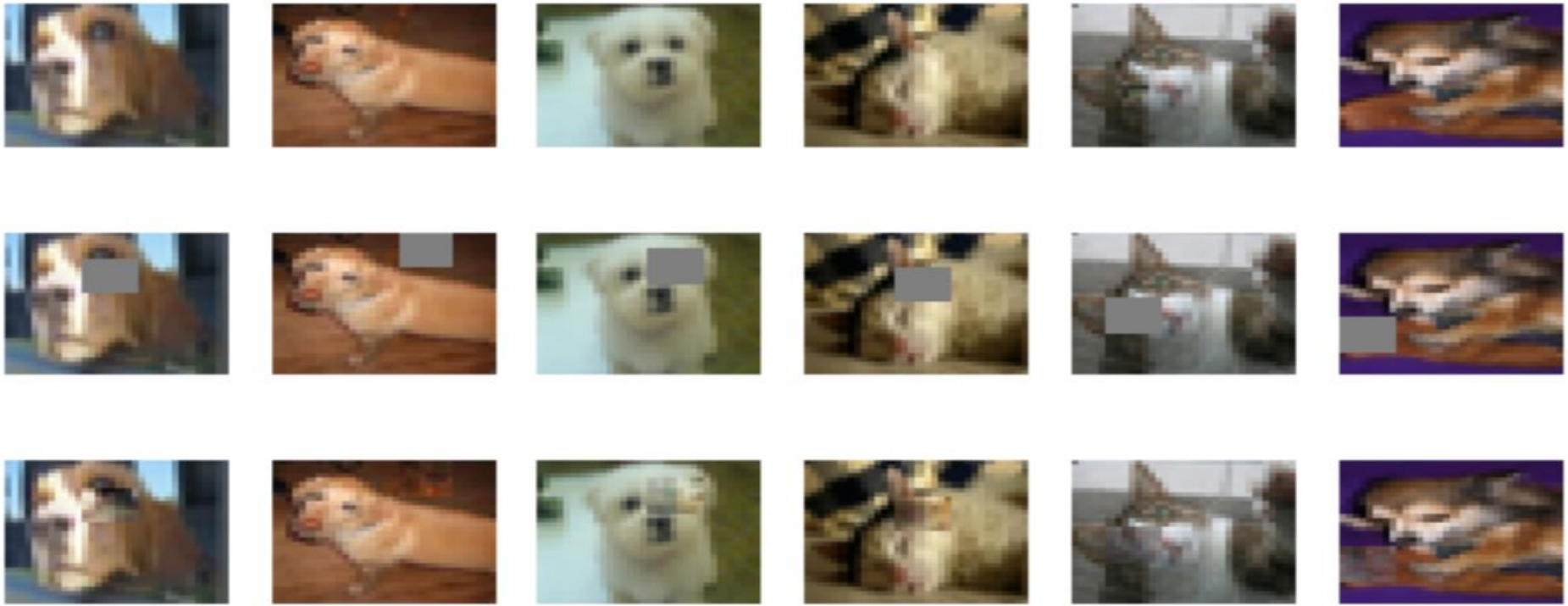


Iteration :10100

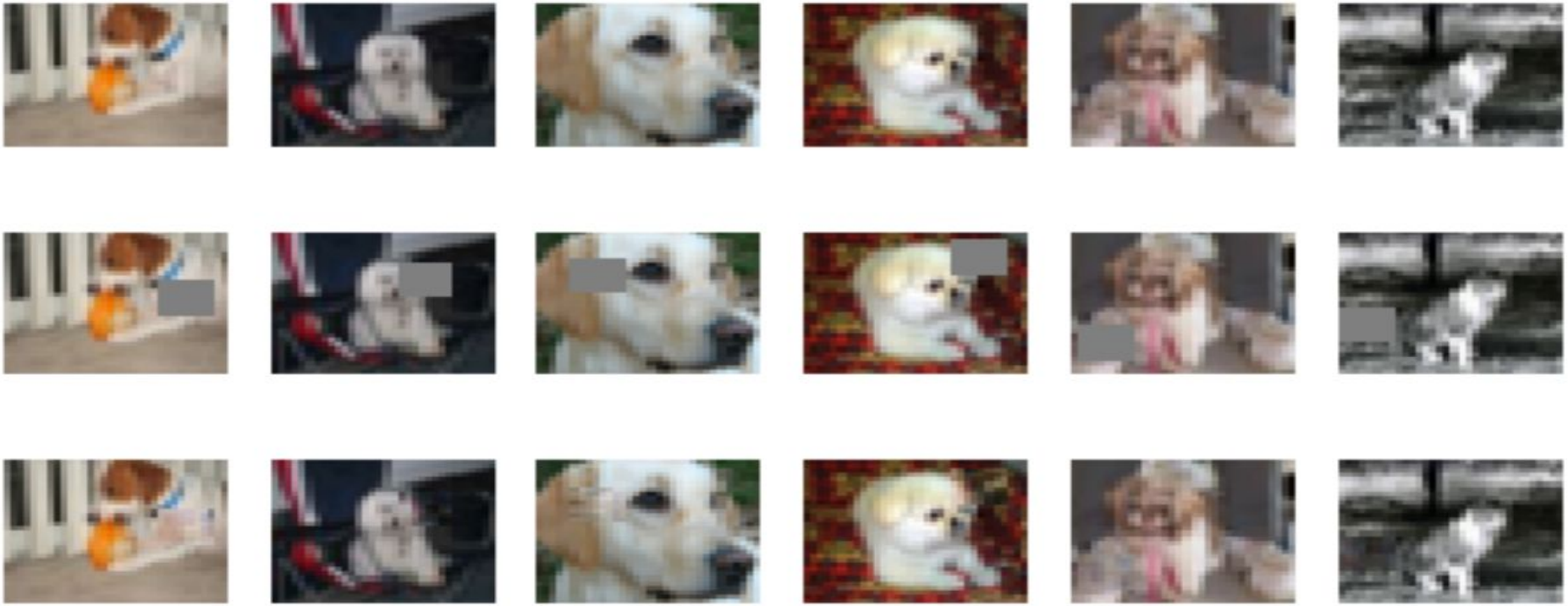
Iteration :15500



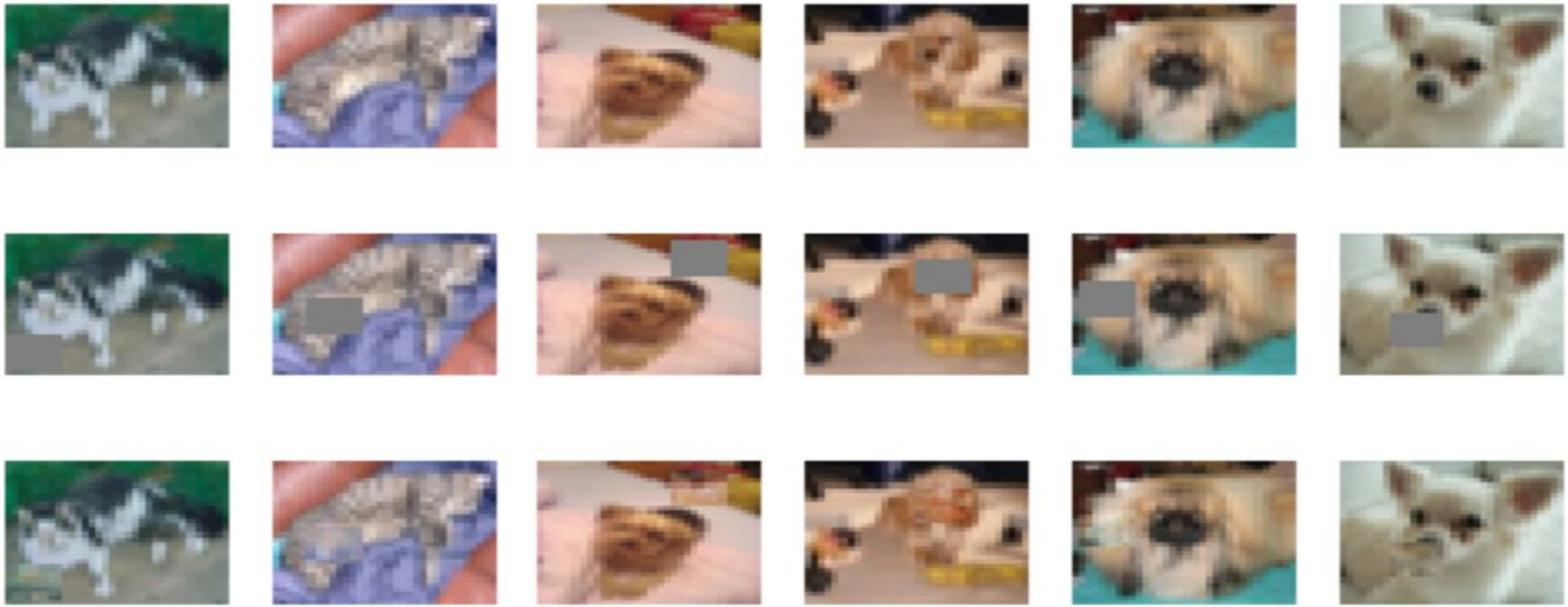
Iteration :20900



Iteration : 29300



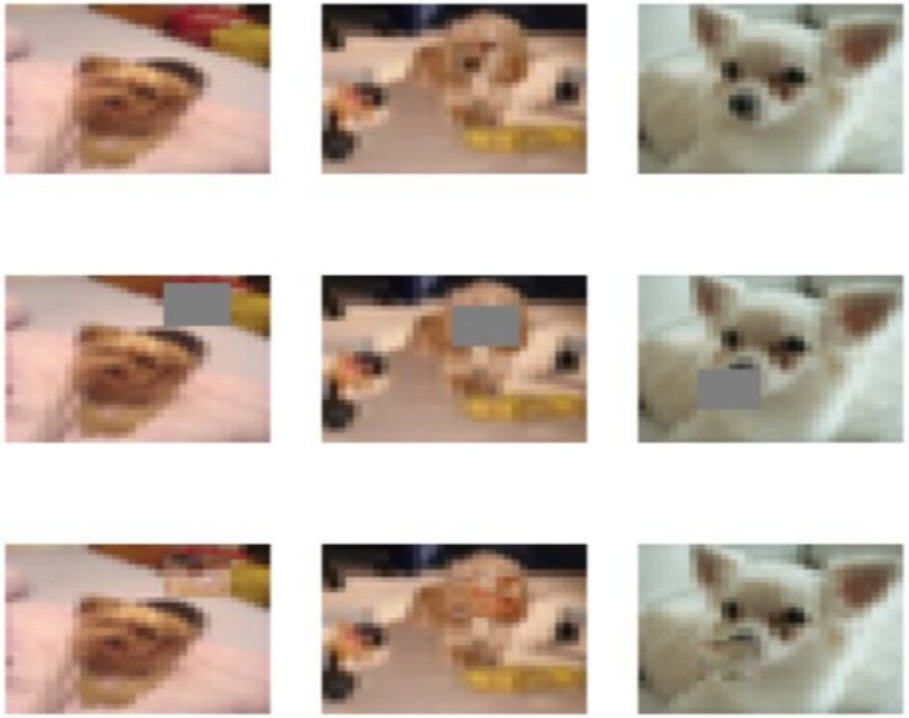
Iteration : 29900



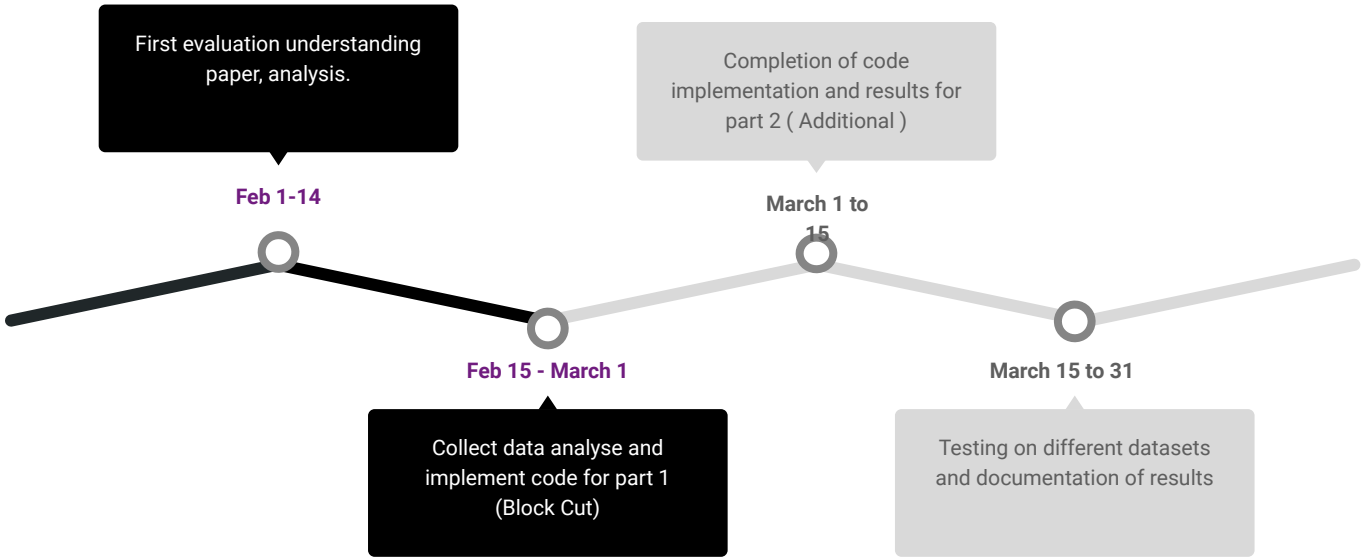
Fails !!

Where the prediction fails ?

The prediction goes a little awry when the shaded block or the removed part of the image has mixed neighbours of both the animal and its background.



Timeline


First evaluation understanding paper, analysis.
Feb 1-14
Completion of code implementation and results for part 2 (Additional)
March 1 to 15
Feb 15 - March 1
Collect data analyse and implement code for part 1 (Block Cut)
March 15 to 31
Testing on different datasets and documentation of results