Tunable Models for Image Processing

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1 Introduction

Deep convolutions neural network has demonstrated its capability of learning a deterministic mapping for the desired imagery effect. However, the large variety of user flavors motivates the possibility of continuous transition among different output effects.

For example if our task is image denoisng, the most common method is by supervised models (deep learning), when the input is a noisy image, and the output will be the clean image (fixed pre-determined corruption level). However, models are optimized for only a single degradation level, so if we have a batch of noisy images with different Gaussian noise, our model will not clean the images well (in reality, the degradation level is not known and at inference time, the model can under-perform).

In order to overcome this limitation, continuous-level based models have been proposed. in such models, the output image is based on a target parameter which can be adjusted at inference time.

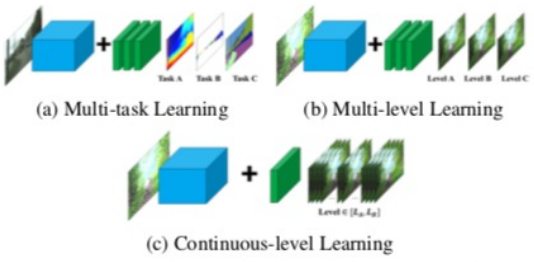


Figure 1: Introduction Description

2 Related Work

2.1 DNI - Deep Interpolation Network

2.1.1 Main Idea

Continuous imagery effect transition is achieved via linear interpolation in the parameter space of existing trained networks (for $numbernets \geq 2$). provided with a model for a particular effect A, they fine-tune it to realize another relevant effect B. DNI applies linear interpolation for all the corresponding parameters of these two deep networks (basically for the filters, normalization (IN) and the biases).

2.1.2 Network Interpolation

If you train two models from scratch on the same task, and perform visualization of the filters (first and last filters), It can be seen that the order of the filters is different but their representation is similar (though not in the same order). Fine-tuning, however, can help to maintain the filters's order and pattern. The "high correlation" between the parameters of these two networks provides the possibility for meaningful interpolation.

In **Figures 2** it can be seen that the filters for different types of noise is strong correlated and when fine-tune several models for relevant tasks (different types of noise) from a pretrained one (N20), the correspondingly learned filters have intrinsic relations with a smooth transition, measuring the correlation between two filter (similar to the Pearson correlation) results close relationship among the learned filters, exhibiting a gradual change as the noise level increases.

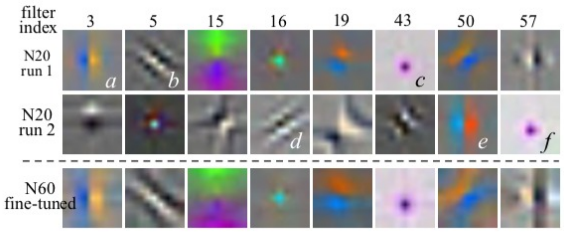


Figure 2: Filter correlations. The first two rows are the filters of different runs (both from scratch) for the denoising (N20) task. The filter orders and filter patterns in the same position are different. The *fine-tuned* model (N60) ($3rd$ row) has a "strong correlation" to the pre-trained one ($1st$ row).

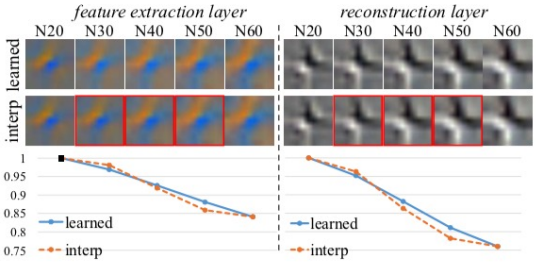


Figure 3: Filters with gradual changes. We show one representative filter for each layer. **$1st$ row**: The fine-tuned filters for different noise level show gradual changes. **$2nd$ row**: The interpolated filters (with red frames) from the N20 and N60 filters could visually fit those learned filters well. **$3rd$ row**: The correlation curves for learned and interpolated filters are also very close.

Figure 2: Filter Visualization (left) and filter gradual changes in different noises (right)

2.1.3 Training

In the paper they trained a model on some task (e.g. denoising), at first they trained a model from scratch on a certain type of noise (Gaussian with some standard deviation), then after the training they did fine-tuning to a different noise (Gaussian with standard deviation - last level).

2.2 AdaFM - Adaptive Feature Modification

2.2.1 Main Idea

The additional module, namely AdaFM layer, performs channel-wise feature modification, and can adapt a model to another restoration level with high accuracy. the aim is to add another layer to manipulate the

statistics of the filters, so that they could be adapted to another restoration level.

Adaptive Feature Modification (AdaFM) layers are inspired by the recent normalization methods in deep CNNs, but in contrast AdaFM layer is independent of either batch or instance samples, filter size and position of AdaFM layers are flexible, the interpolation property of AdaFM layers could achieve continual modulation of restoration levels.

Because there are "high correlation" between the filters of the networks (as we saw in DNI), we can think of a function that performs the match between them those filters. To further reveal their relationship, they use a filter to bridge the corresponding filters - g (done by depth-wise convolution layer after each layer).

In addition, the filter g is gradually updated by gradient descent, so we can obtain the intermediate filter to get smooth transition.

In **Figures 3** we can see the architecture of AdaFM-Net.

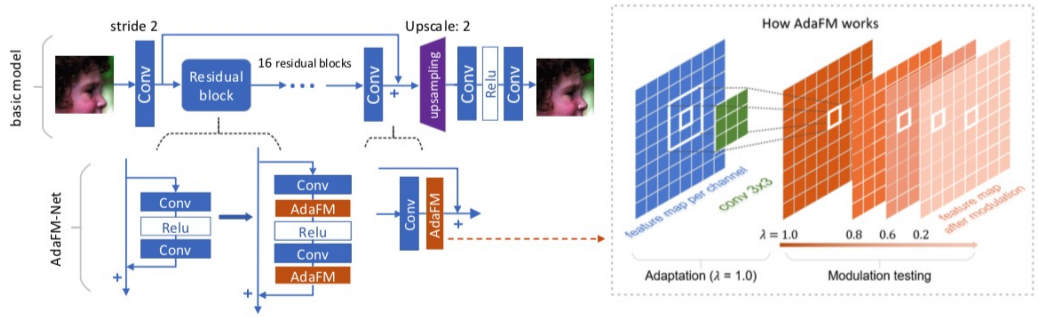


Figure 4. The left part presents the basic model and the AdaFM-Net. The right part shows how AdaFM works in the adaptation process and the modulation testing.

Figure 3: AdaFM-Net

The model mainly deals with restoration tasks (e.g denoisng, SR)

2.2.2 Training

Train a basic model and an adaptive model that could deal with level L_a and L_b, respectively. While in modulation testing, they propose a new network that can realize arbitrary restoration effects between level L_a and L_b by modulating certain hyper-parameters.

1. Train a basic network (CNN) for the start restoration level L_a, we call this network N^a_{bas}.

2. Insert AdaFM layers to N^a_{bas} and obtain N_{ada}. fixing the parameters of N^a_{bas}.

3. Optimize the parameters of AdaFM on the end level L_b (finetuning the AdaFM layers)

2.2.3 Interpolation

We can obtain the intermediate filter f_{mid} by the following function: $f_{mid} = f_{15} + \lambda(g - I) * f_{15}, \lambda \in [0, 1]$ where λ is an interpolation coefficient.

During the modulation testing, the interpolation is performed between the identity filter and the learned AdaFM filter. If there is a residual structure, you don't have to look for a 1x1, 3x3 or 5x5 identity filter but just interpolate the parameters of transformer (conv2D).

$$AdaFM(x) = g(x) = \underbrace{transformer(x)}_{\text{g'(x)}} + x = (1 + g') \cdot x$$

$$f_{mid} = f_{15} + \lambda(g' * f_{15}) = f_{15} + \lambda(g - I) * f_{15}$$

They initialized AdaFM layers with identity filters I and zero biases, which is regarded as the start point of AdaFM layers. we can linearly interpolate the parameters of AdaFM layers as:
$g_i* = I + \lambda(g - I)$ where g_i* is interpolated filter

2.2.4 Adaptation Accuracy

according the paper as the AdaFM-Net is optimized from L_a to L_b, they name this process as adaptation, and use adaptation accuracy to denote its performance.

There are 3 factors that affect this adaptation accuracy:

- Filter Size - a larger filter size or more parameters will lead to better adaptation accuracy.
- Direction - From easy to hard is a better choice.
- Range - The smaller of the range/gap (L_a - L_b), the better the adaptation accuracy.

In **Figures 4** we can see some results.

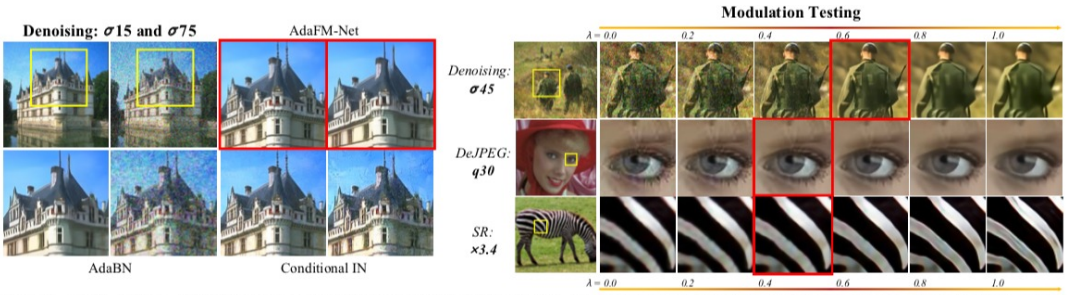


Figure 6. Left: Artifacts on the output images produced by AdaBN and conditional instance normalization. Right: Modulation testing in Denoising (CBSD68), DeJEPG (LIVE1) and Super Resolution (Set14 [21]).

Figure 4: AdaFM-Net Results

3 Model Comparison

- **AdaFM** - The layer is a linear transition block with depth-wise convolution. Due to the linear interpolation method, it might also fail to overcome non-linear interpolation requirements. Therefore, it is not appropriate for more complex tasks such as the perception-distortion (PD) trade-off in restoration or style transfer.
- **DNI** - At inference time, it linearly interpolates all the parameters of the networks. can fail when the required interpolation is not linear. fine-tuning the network without any constraint cannot consider the initial level, which might lead to a degraded performance at intermediate levels.
- **FTN** - Enables interpolation of the kernel between initial and final one in a non-linear manner

In **Figures 5** we can see the Model Comparison to 4 categories. it can be seen that:

1. AdaFM works mainly for restoration tasks and for other task (e.g Style Transfer) the adaption won't be good.
2. DNI requires extra memory to save temporary network parameters and requires a third interpolated network for the inference. in addition fine-tuning process of the DNI simply updates the parameters, without considering the initial state. Therefore, the relation between the parameters for the two levels becomes weaker
3. CFS-Net and Dynamic Net propose frameworks that interpolate the feature maps using tuning branches and tuning this branches requires large memory and heavy computations.

	No Extra Memory	Non-linear Adaptation	Efficient	Regularized
AdaFM [12]	✓	✗	✓	✓*
DNI [33,34]	✗	✓	✗	✗
Dynamic-Net [30]	✓	✓	✗	✗
CFSNet [32]	✓	✓	✗	✗
FTN (Ours)	✓	✓	✓	✓

Figure 5: Comparison - Taken from FTN paper

In **Figures 6** we can see that on denoising task DNI works the best (in a CNN network of 10 blocks). However when testing it on Ada-FM-Net (CNN network of 16 blocks) FTN works the best.
In addition we can see that the number of parameters and the computation for FTN and AdaFM (for several tasks) is relative small.

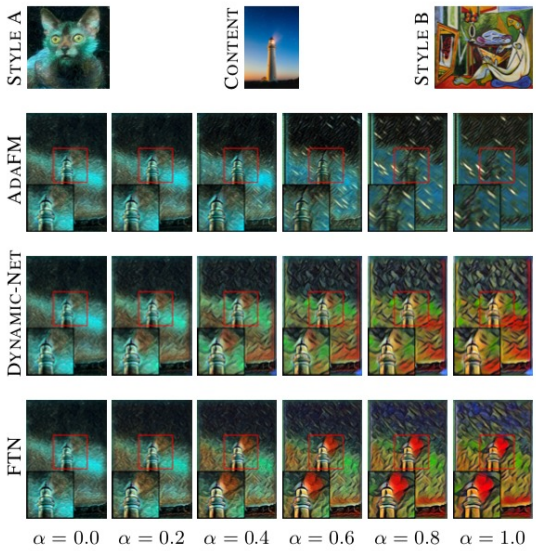
Table 3: Overall computations, relative computations from baseline (in percentage), and number of parameters of the frameworks. Setting and network configurations are described in Sec. 4.1

Task	Denoising		×2 Super-Resolution		Style Transfer	
Network	AdaFM-Net		CFSNet-30		Transform-Net [15]	
	GFLOPs	Params(M)	GFLOPs	Params(M)	GFLOPs	Params(M)
Baseline	25.11	1.41	155.96	2.37	40.42	1.68
+ CFSNet [32]	46.96 (87.02%)	3.06	311.36 (99.64%)	4.93	-	-
+ AdaFM [12]	26.01 (3.58%)	**1.46**	162.50 (4.20%)	**2.47**	41.73 (3.24%)	**1.72**
+ Dynamic-Net [30]	-	-	-	-	62.24 (53.98%)	2.59
+ **FTN**	**25.36 (0.10%)**	1.83	**156.34 (0.02%)**	3.01	**40.86 (1.09%)**	2.06
+ **FTN(G=16)**	**25.13 (0.01%)**	**1.44**	**156.00 (0.00%)**	**2.41**	**40.46 (0.10%)**	**1.70**

Table 2: **Gaussian Denoising Results.** Average PSNR (dB) on CBSD68 test dataset. Unseen noise levels are denoted with *. The best results are **bold-faced** and the second best results are underlined.

	CFSNet-10 (10 Blocks)				AdaFM-Net (16 Blocks)			
Noise Level	20	40*	60*	80	20	40*	60*	80
From Scratch	32.42	28.98	27.13	25.90	32.44	28.90	26.92	25.60
DNI	**32.42**	**28.87**	**27.01**	**25.96**	**32.44**	28.20	26.98	25.97
AdaFM	**32.42**	28.48	26.75	25.84	**32.44**	28.17	26.77	25.96
CFSNet	**32.42**	28.65	26.95	25.93	**32.44**	28.41	26.87	26.00
FTN-gc16	**32.42**	28.77	**27.01**	25.89	**32.44**	**28.78**	**27.05**	25.98
FTN-gc4	**32.42**	28.65	26.90	25.90	**32.44**	28.64	26.95	26.00
FTN	**32.42**	28.45	26.86	25.93	**32.44**	28.48	26.89	**26.03**

Figure 6: Comparison between the models - computation memory (left) Denoising Task (right)



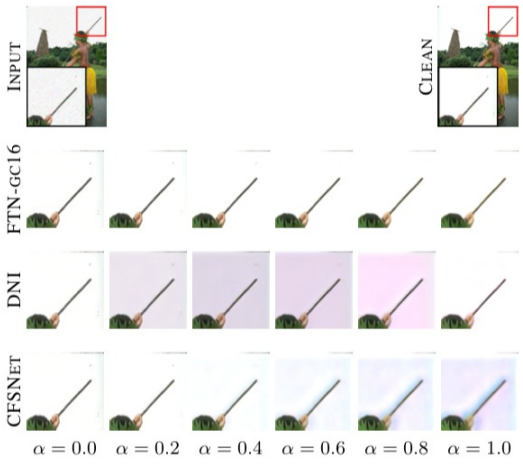


Figure 8: **Denoising results on weak noise level ($\sigma = 20$). When user controls α to a large value, over-smoothing artifacts arise**

Figure 7: FTN gets better result in denoising task (right) and for mixing style (left)

4 Implement Smoother Network Tuning and Interpolation for Continuous-level Image Processing paper

To get a better intuition about Continuous-level models, I implemented Modulating Image Restoration with Continual Levels via Adaptive Feature Modification Layers (CVPR 2019) and DNI - Deep Network Interpolation for Continuous Imagery Effect Transition (CVPR 2018)

I have implemented the FTN paper by Samsung Research (2020, with no code reference. The proposed architecture learns kernels during training (taken from the idea in a hyper networks paper).

4.0.1 Introduction

To deal with Continuous-level problems, several frameworks have been proposed, and they have the following steps in common. In the training phase, they train their CNN network twice for each level. The first-training is similar to the general network training method. During the second-training, some parameters that were optimized in the first-training are fixed, and the other parameters are fine-tuned or some additional modules are trained for the second level.
In the test phase, they make their networks available at any intermediate level with their own interpolation methods.
Although various network tuning and interpolation frameworks have been proposed, deeper analysis and stable generalization for practical usage are required.

In the paper they proposed a smoother network tuning and interpolation method for Continuous-level using the FTN, which is structurally smoother than the other frameworks. In addition, the method is comparable in adaptation and interpolation performance on multiple imaging levels, significantly smoother in practice, and efficient in both memory and computational complexity.

4.0.2 Main Idea

Filter Transition Network (FTN) which is a non-linear module that easily adapts to new levels (and a method to initialize non- linear CNNs with identity mappings).

FTN takes **CNN filters** as input (instead of image/feature map) and learns the transitions between levels (the modification is non-linear which can better adapt to new level). The FTN layer basically transform the filters of the network.

FTN module in an arbitrary convolutional layer can be described as $Y_i = X_i * \big(f_i^1 \times (1-\alpha) + FTN(f_i^1) \times \alpha\big)$, where X_i and Y_i are the input and output of the i-th convolution layer, f_i^1 is the corresponding kernel, and α is control parameter.

In **Figures 12** we can see the architecture of FTN.

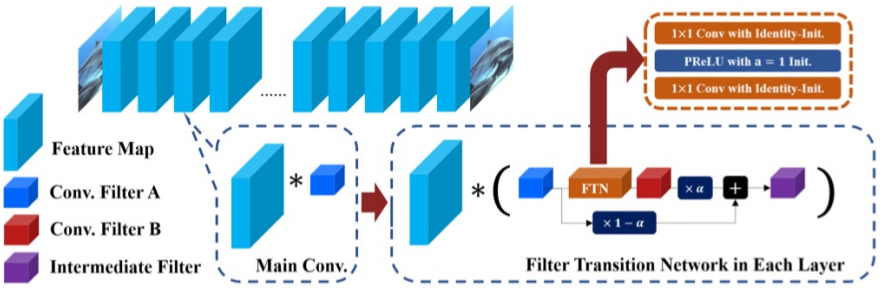


Figure 2: Network architecture of the proposed Filter Transition Network (FTN) when adapted in arbitrary main convolutional networks. Filter of main network (blue) is transformed via FTN for other levels (red). In inference phase, interpolated filter (purple) is used for intermediate levels

Figure 8: FTN

4.0.3 Training

- Train the main network for the initial level with $\alpha = 0$.
- Freeze the main network and train the FTN only for the second level with $\alpha = 1$ (breaks skip-connection).
- At inference time, we can interpolate between two kernels (levels) by choosing $\alpha \in [0, 1]$.

FTN learns the transition itself, and can approximates kernels of the second level (because we optimize only its parameters during the second level)

4.0.4 Initialization of FTN

Init the filter and the activation(PReLU with a=1) as the identity (for keeping the network works for the initial level).

4.1 Experiments

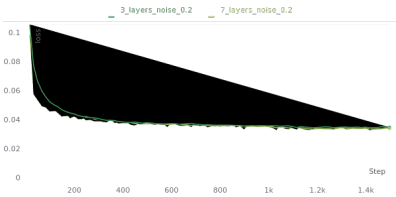
During the implementation of the article I began to conduct experiments on the task of cleaning noise with a different noise between the two stages.
Because I used relatively simple architectures, to train the model on the resources allocated to me, the results did not yield good enough results, so we could not perform an interpolation of the kernels to justify noise cleaning at different noise levels.

4.1.1 FTN- Densioing Task

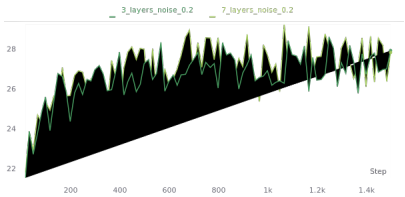
4.1.2 1st Step

Train a renset model (with 5-10 layers) on denoising task. added a Gaussian noise with std equal to 0.2 to each image. I've added the FTN blocks after each filter, In the first training alpha=0 (we don't learn the FTN blocks because the gradient is 0). the results were the same to the basic model (PSNR 27-28). It can be seen that with the architecture of the model on 16 layers, the model tries to clear a noise of 0.2, but does not maintain the sharpness of the original images.

(a) Image Denoising Resnet 5-10 layers



(b) Training Loss



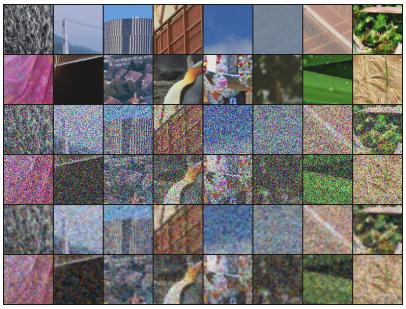
(c) PSNR

Figure 9: Denoising Task First Step

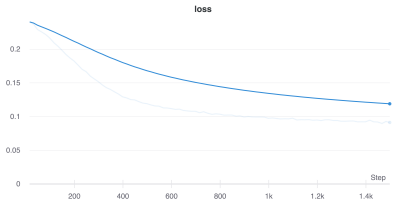
4.1.3 2nd Step

Finetune the model on Gaussian noise with std equal to [0.5, 0.6], alpha=1 while freezing the weights of the model (beside the FTN layers, which responsible to learn the transition between the kernels on each noise), At first the loss didn't converge, but after the initialization of the ftn kernel as idenety and the bias to zero the error has converged to a certain limit (which in my opinion is not good enough).

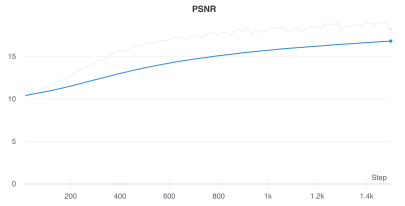
Results during Finetune the model on 0.5 std noise:



(a) Finetune



(b) Training Loss



(c) PSNR

Figure 10: Denoising Task Second Step

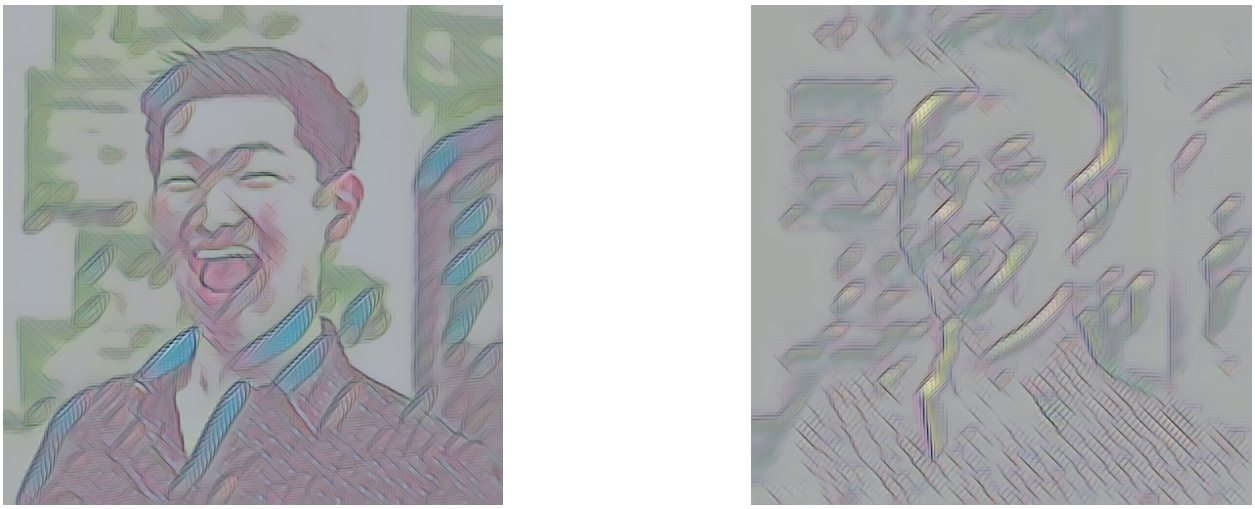
I think the model's architecture (resnet with blocks that contain filter, BN and relu) is not good enough, regardless of the number of layers of the model (I tried several layers and the difference is very negligible), it fails to bring good enough results in finetune. I have read about a number of papers and may have tried to implement the DcNN model but I it won't meet our conditions. With more resources, I could have managed the optimization of the model better, and arrived at a model that gets good results.

4.1.4 FTN- StyleTransfer Task

Because the noise cleaning model did not work adequately, it was difficult to see whether during interpolation in the model's parameters space, it clears noise with unlearned noise (level between the start level and the end one). Therefore, we chose to test the model on the style task (adding style to the image) - will allow us a clearer distinction.

At first I implemented the paper "Arbitrary Style Transfer in Real-time with Adaptive Instance Normalization", and tested it without adding the FTN blocks.

4.1.5 1st and 2nd Steps



(a) Finetune

(b) Training Loss

Figure 11: feathers Style to Mosaic style - First Step

Additional results and training error graphs can be seen at the end of the report (Appendix Part).

5 Implementation Dynamic-Net: Tuning the Objective Without Re-training for Synthesis Tasks paper

We cannot directly modify the objective at test-time. However, what we can do is modify the latent space representation. Therefore, their approach relies on manipulation of deep features in order to emulate a manipulation in objective space.

The main advantages of the Dynamic-Net are three-fold.

- Using a single training session the Dynamic-Net can emulate networks trained with a variety of different objectives, for example, networks which produce stronger or weaker stylization effects.
- he ability to traverse the objective space at test-time shrinks the search space during training.
- It facilitates image-specific and user-specific adaptation, without re-training.

5.1 MNIST Dataset

First, I implemented the model and trained it on style samples to see if it provides reliable results. Then, I wanted to take an untested task, to see if the model could do it.

The task I was dealing with, is generate digits from 1 to 10 (using the mnist dataset). I used the DCGAN model to generate the images. In the first phase I trained the DCGAN model to generate the digit 3, and in the second phase (the rest of the network is frozen except for dedicated blocks that study the transition between the kernels) I tried to generate the digit 8. The results confirmed my expectation that Moving from digit 3 to digit 8.

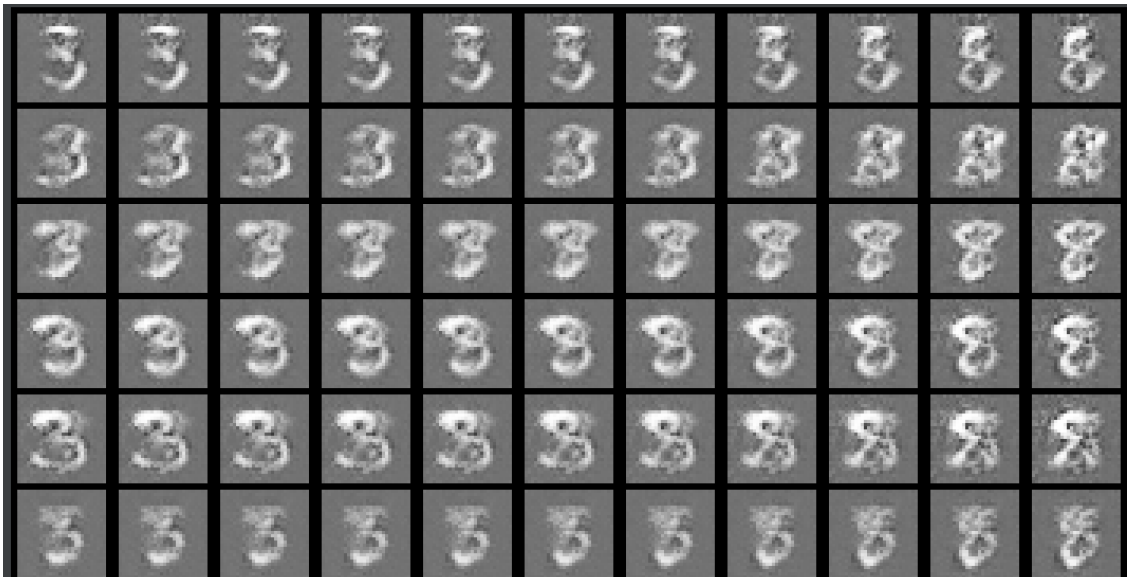


Figure 12: Transition from digit number 3 to digit 8

5.2 Cartoon Dataset

I used Style GAN to perform another task on the model. I thought of an idea that takes a realistic image and gradually transfers it to a cartoon image while using the above mode.

The results were not impressive because I did not have the resources to train for a long time. The code is built and works, and it seems that during the first epochs the model learns the transition between one

type of image and another. Unfortunately training takes a long time, and the resources in the cluster are an obstacle.

6 Appendix

6.1 PSNR - Peak Signal to Noise

The term peak signal-to-noise ratio (PSNR) is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation.

Using the same set of tests images, different image enhancement algorithms can be compared systematically to identify whether a particular algorithm produces better results. The metric under investigation is the peak-signal-to-noise ratio. If we can show that an algorithm or set of algorithms can enhance a degraded known image to more closely resemble the original, then we can more accurately conclude that it is a better algorithm.

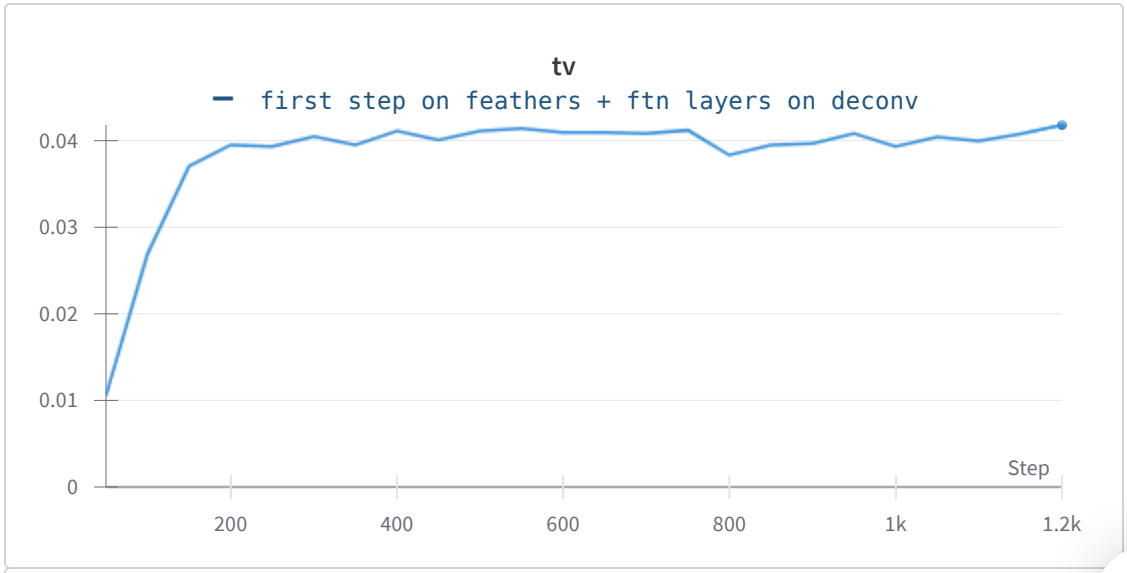
$$PSNR = 20 \log_{10} \left(\frac{MAX_f}{\sqrt{MSE}} \right)$$

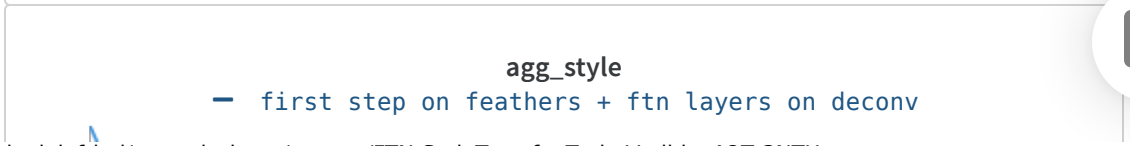
Figure 13: PSNR- MAX_f is the maximum signal value that exists in the original image

FTN- StyleTransfer Task

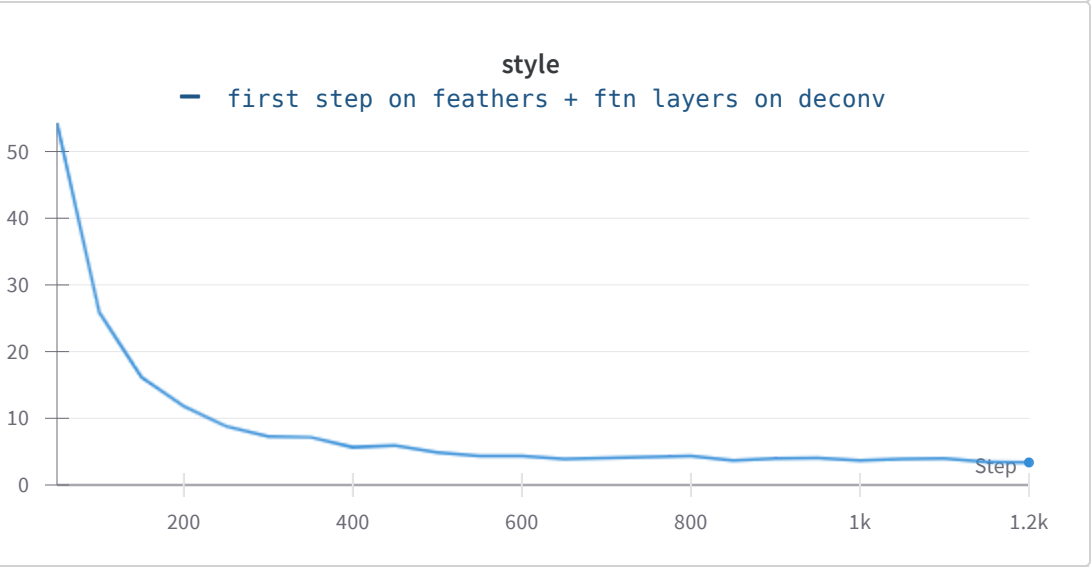
Daniel Afrimi

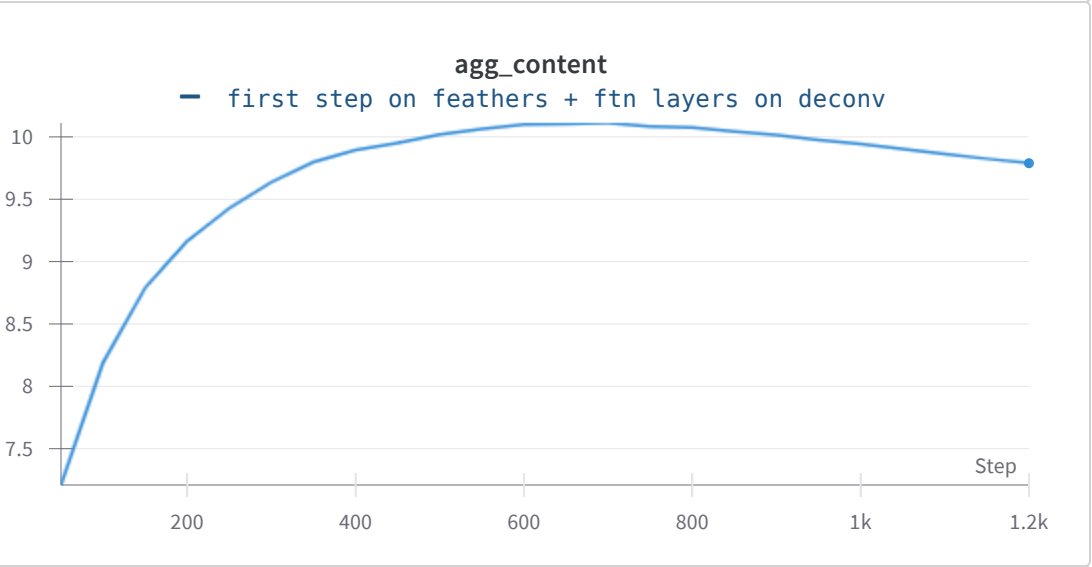
Section 1

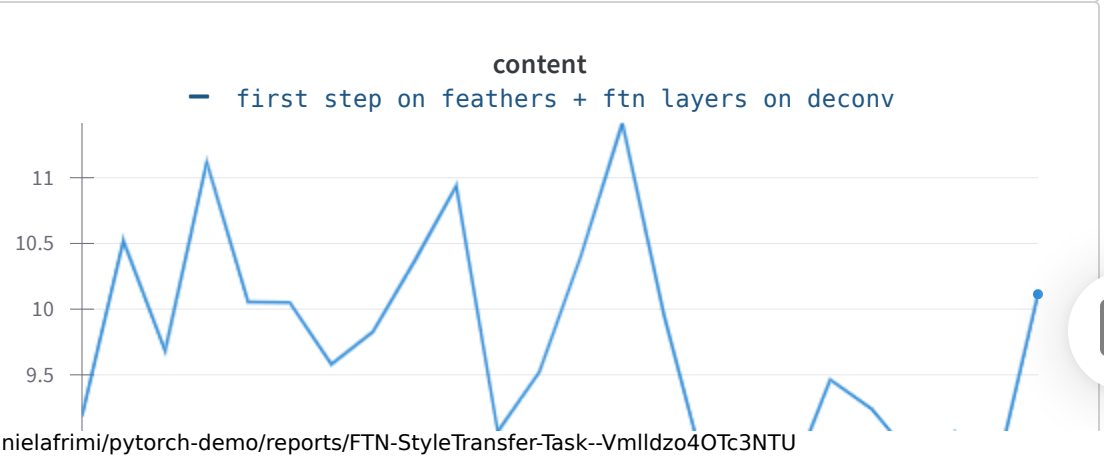




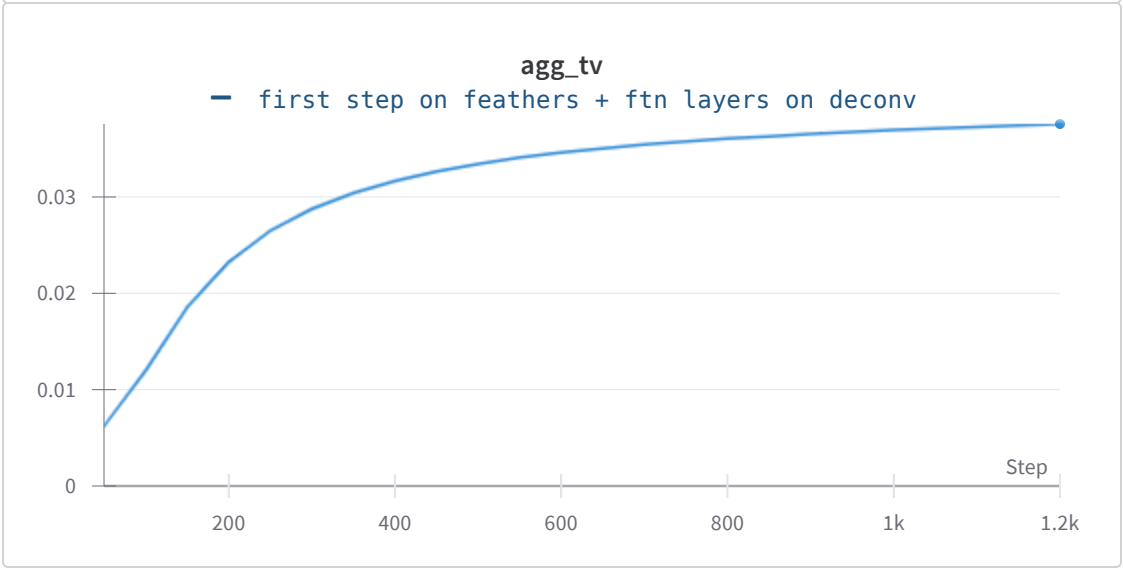

60
40
20
0
Step
200
400
600
800
1k
1.2k

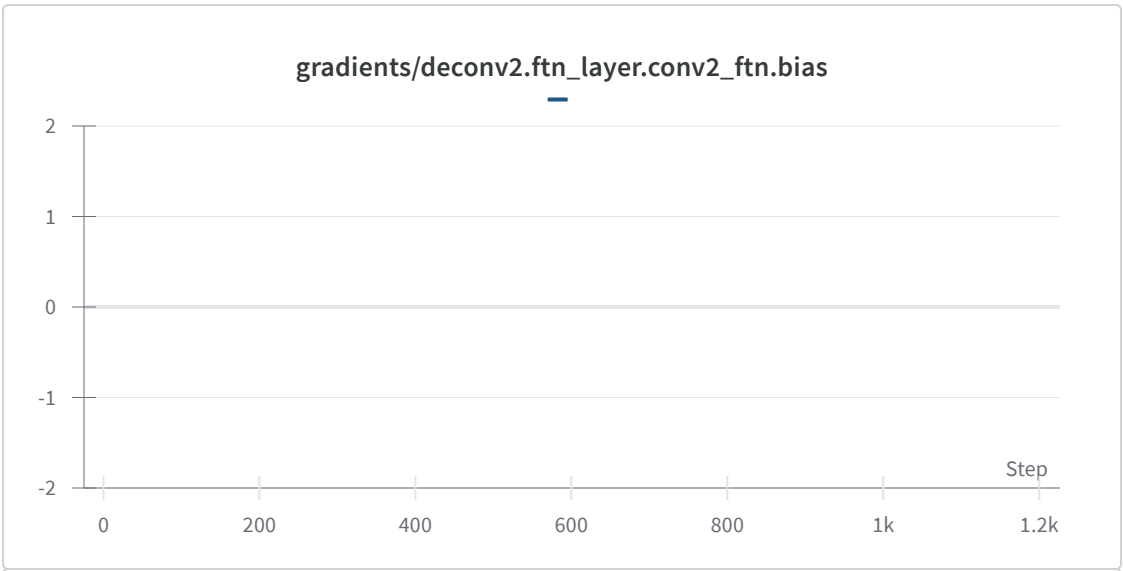

style
first step on feathers + ftn layers on deconv
50
40
30
20
10
0
Step
200
400
600
800
1k
1.2k


agg_content
first step on feathers + ftn layers on deconv
10
9.5
9
8.5
8
7.5
Step
200
400
600
800
1k
1.2k

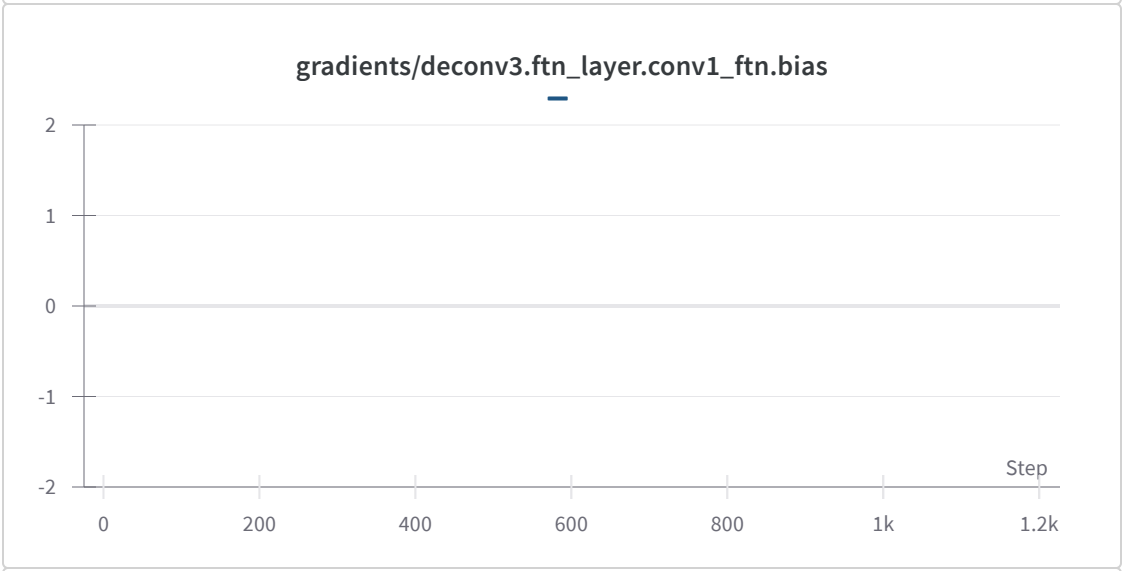

content
first step on feathers + ftn layers on deconv
11
10.5
10
9.5


9
Step
200
400
600
800
1k
1.2k


agg_tv
first step on feathers + ftn layers on deconv
0.03
0.02
0.01
0
Step
200
400
600
800
1k
1.2k


gradients/deconv2.ftn_layer.conv2_ftn.bias
2
1
0
-1
-2
Step
0
200
400
600
800
1k
1.2k


gradients/deconv3.ftn_layer.conv2_ftn.weight
2
1
0
-1
-2
Step
0
200
400
600
800
1k
1.2k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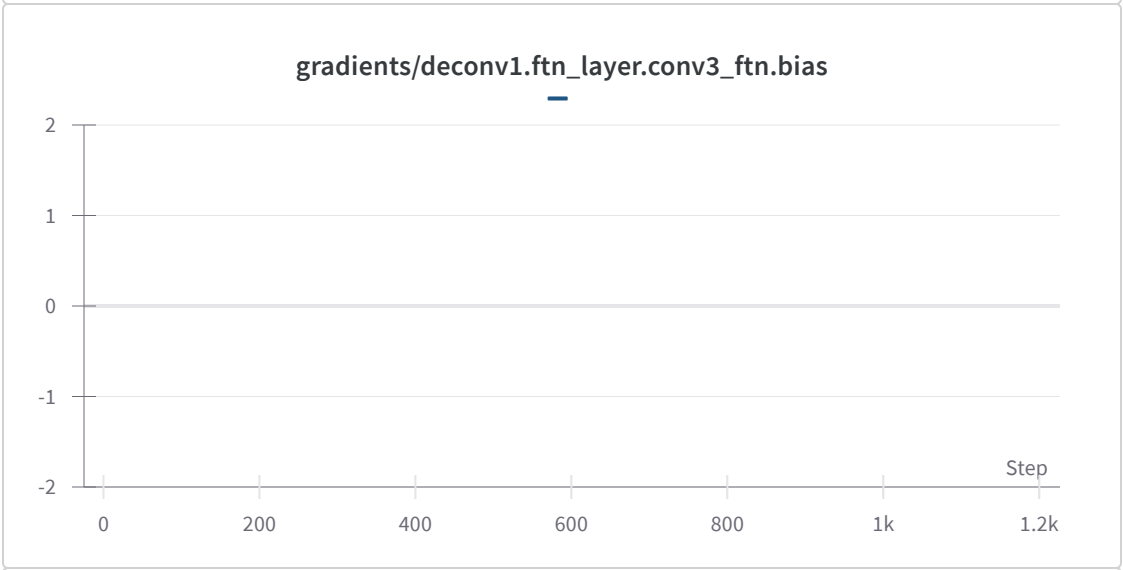
1
0
-1
-2
Step
0
200
400
600
800
1k
1.2k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-1
-2
Step
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400
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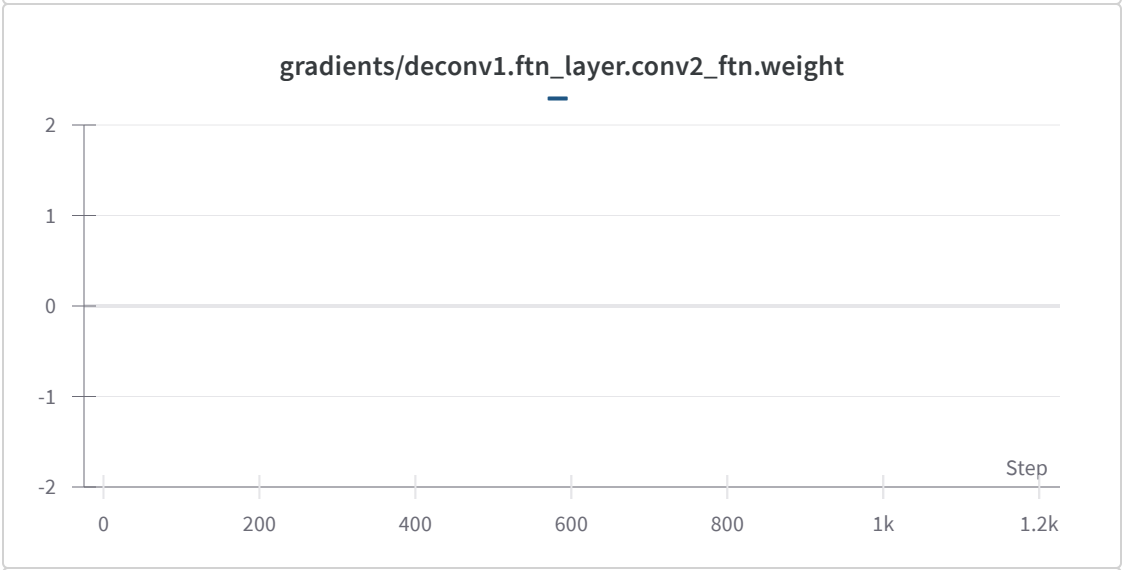
1.2k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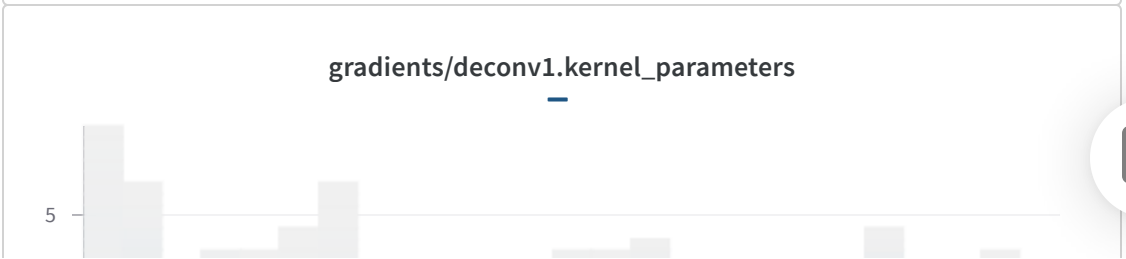
2
1
0
-1
-2
Step
0
200
400
600
800
1k
1.2k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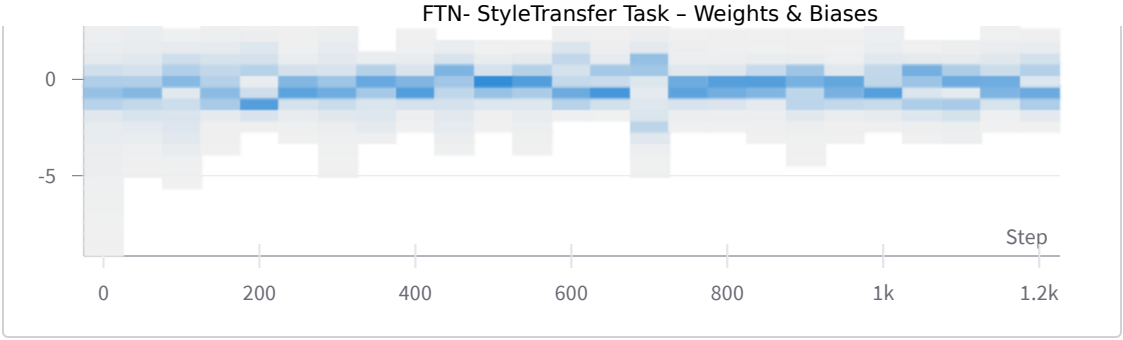
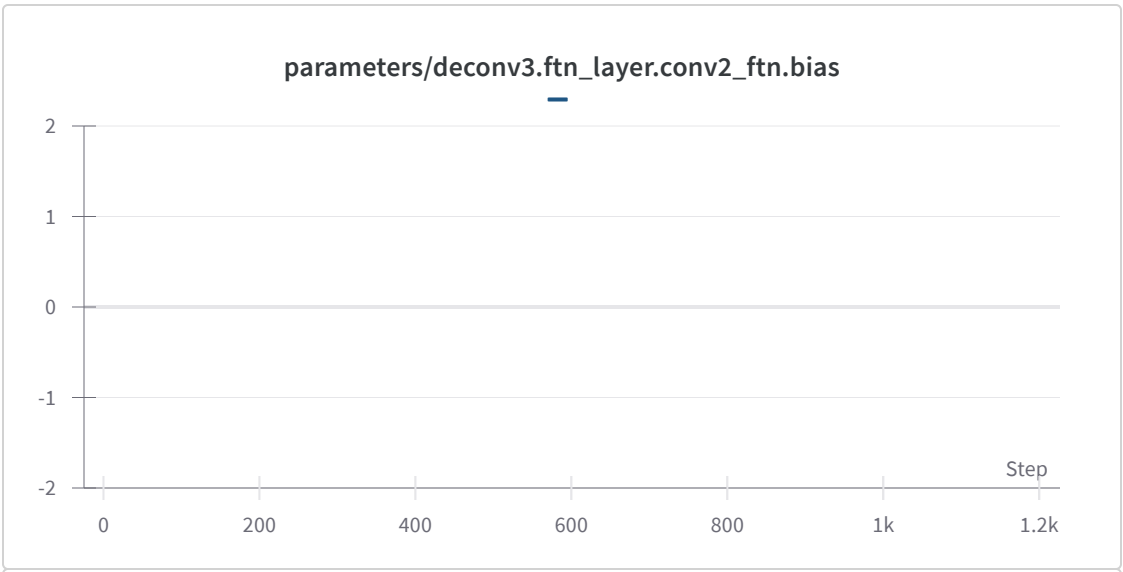
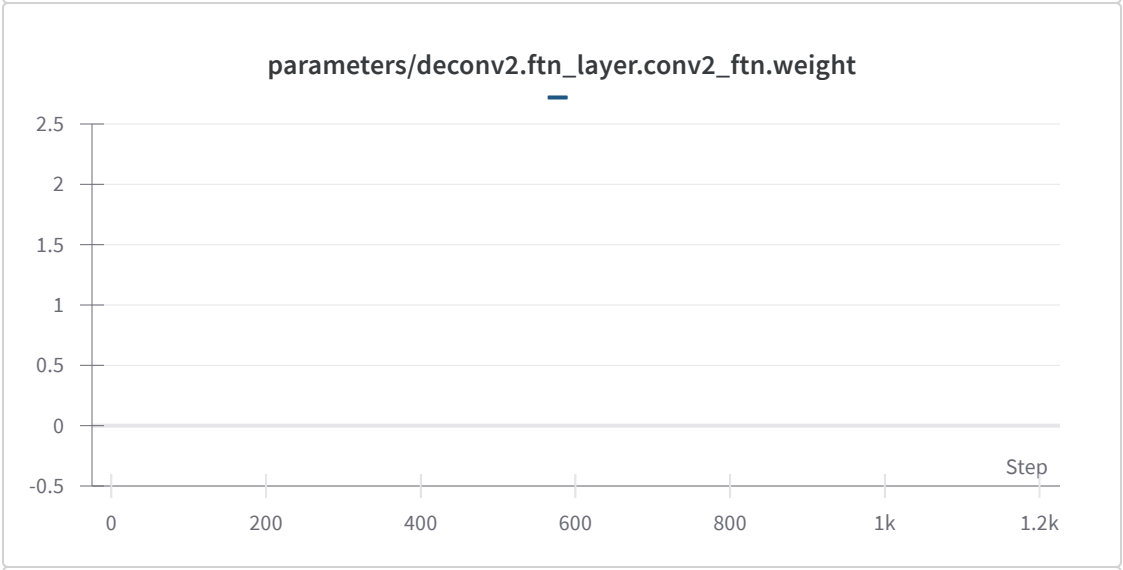

0
-5
Step
0
200
400
600
800
1k
1.2k


parameters/deconv3.ftn_layer.conv2_ftn.bias
2
1
0
-1
-2
Step
0
200
400
600
800
1k
1.2k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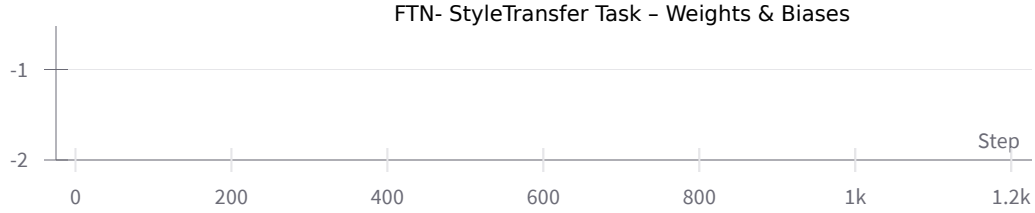
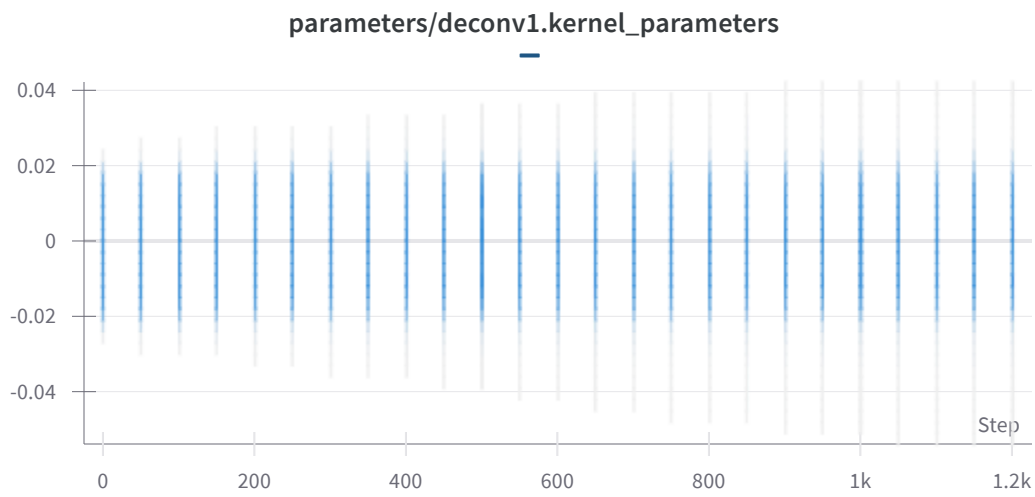
2.5
2
1.5
1
0.5
0
-0.5
Step
0
200
400
600
800
1k
1.2k


parameters/deconv3.ftn_layer.conv1_ftn.bias
2
1
0


-1
-2
Step
0
200
400
600
800
1k
1.2k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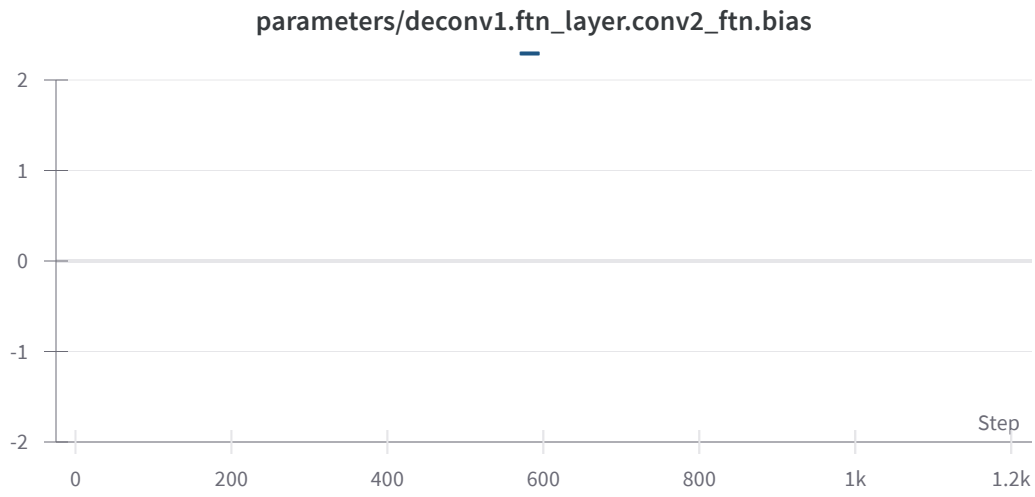
0.04
0.02
0
-0.02
-0.04
Step
0
200
400
600
800
1k
1.2k


parameters/deconv1.ftn_layer.conv2_ftn.bias
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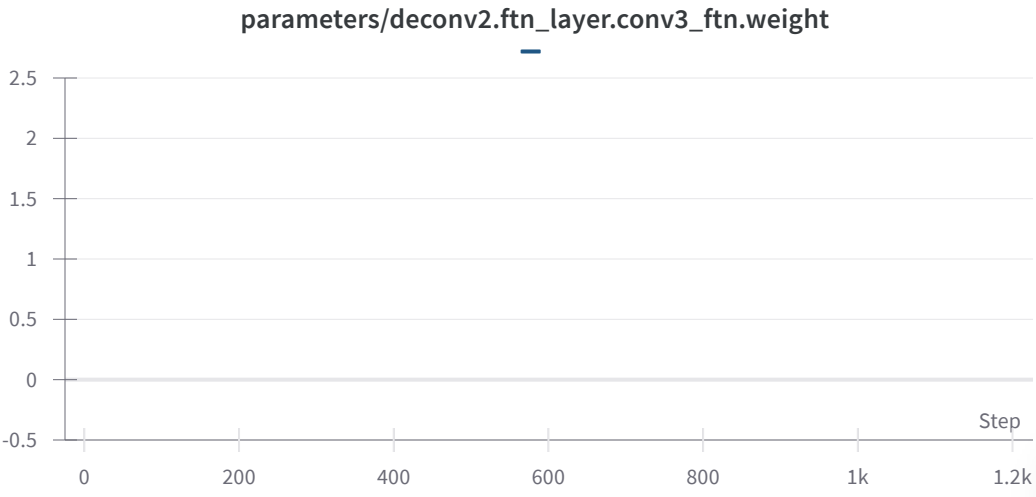
1
0
-1
-2
Step
0
200
400
600
800
1k
1.2k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2.5
2
1.5
1
0.5
0
-0.5
Step
0
200
400
600
800
1k
1.2k

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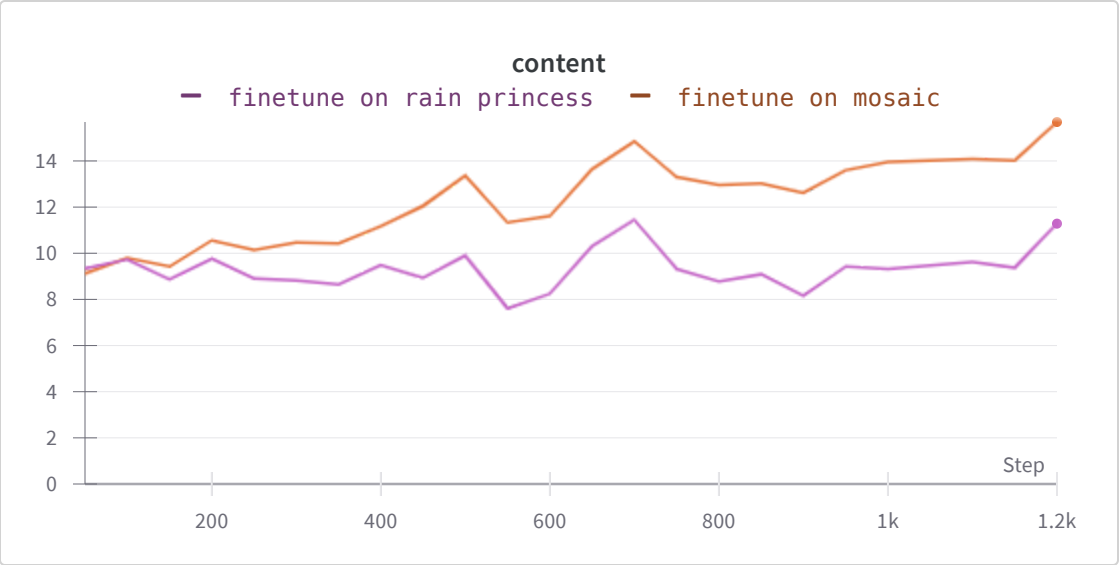
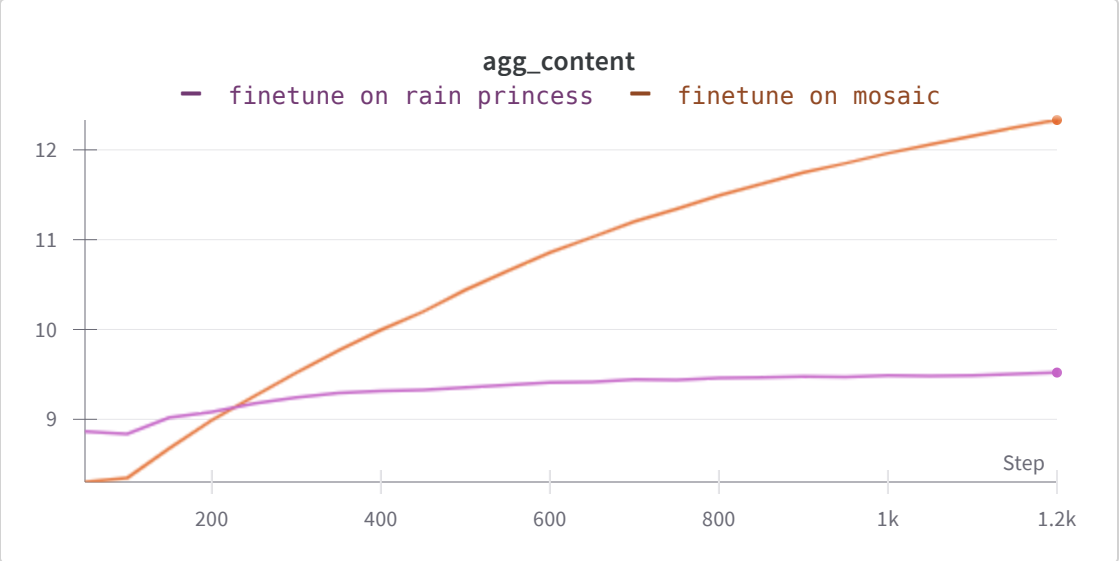
https://wandb.ai/danielafrimi/pytorch-demo/reports/FTN-StyleTransfer-Task--Vmlldzo4OTc3NTU

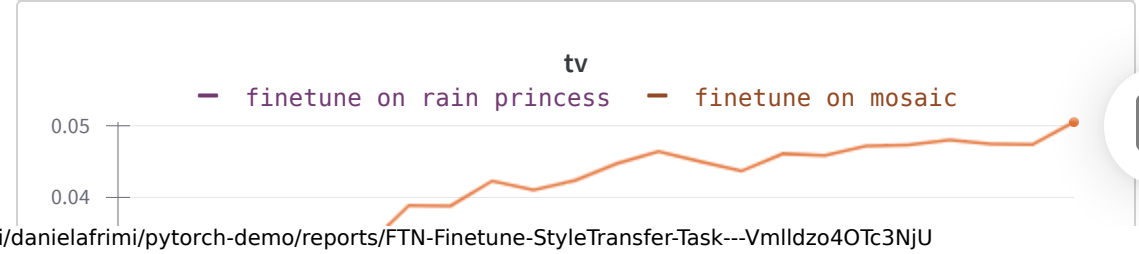
FTN- Finetune StyleTransfer Task

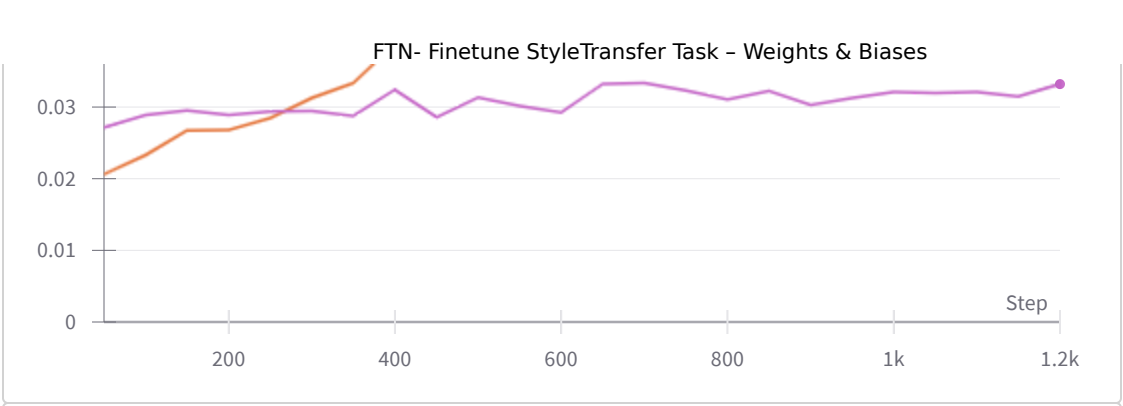
Daniel Afrimi

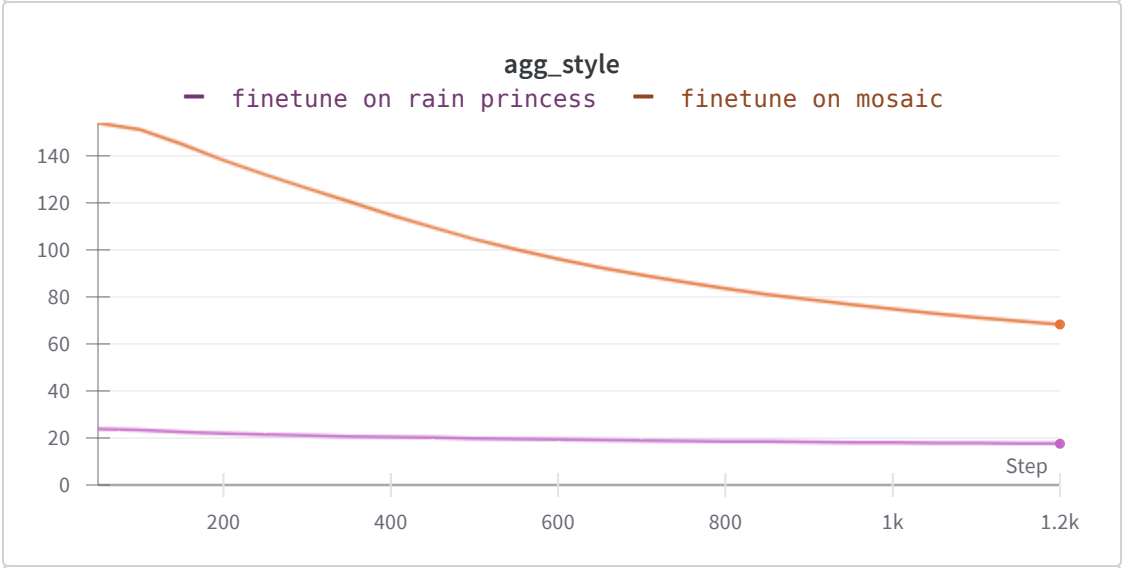
Section 1

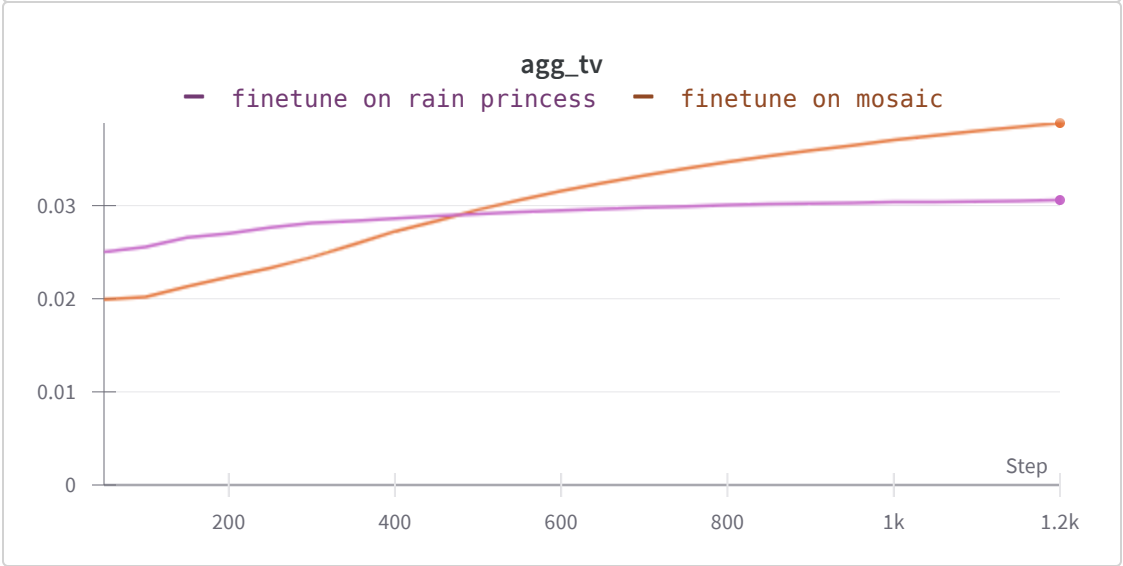


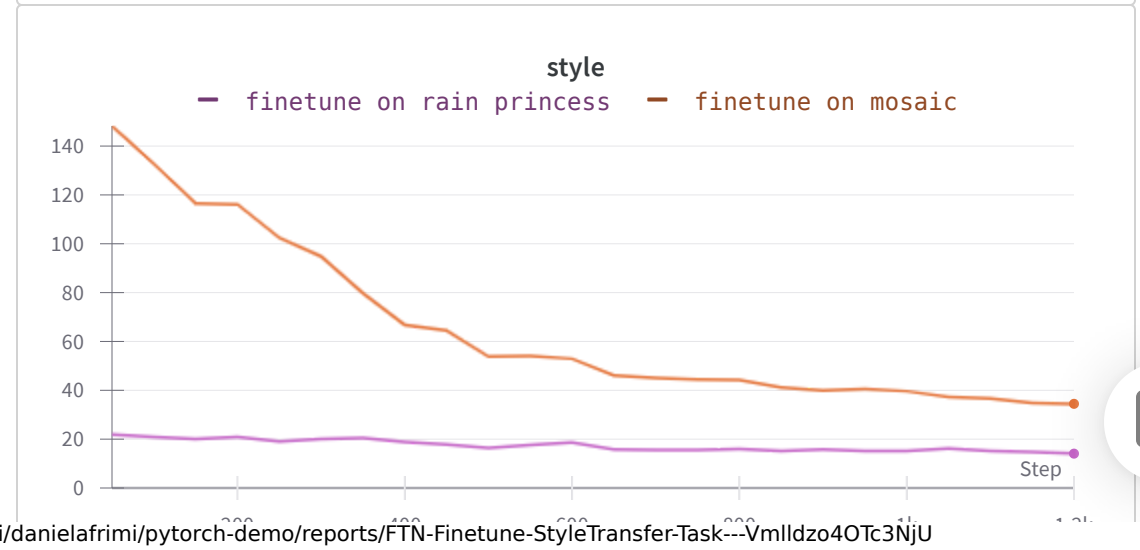





0.03
0.02
0.01
0
Step
200
400
600
800
1k
1.2k


agg_style
finetune on rain princess
finetune on mosaic
140
120
100
80
60
40
20
0
Step
200
400
600
800
1k
1.2k


agg_tv
finetune on rain princess
finetune on mosaic
0.03
0.02
0.01
0
Step
200
400
600
800
1k
1.2k

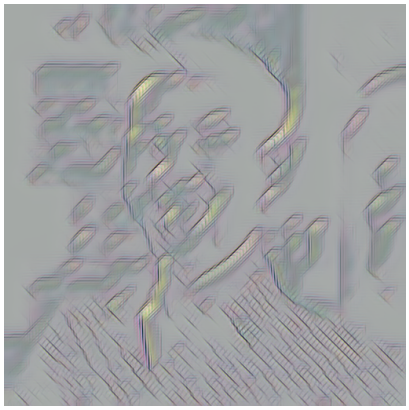

style
finetune on rain princess
finetune on mosaic
140
120
100
80
60
40
20
0
Step

200 400 600 800 1K 1.2K

dan

finetune on rain princess

finetune on mosaic



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