How Much Deep Learning does Neural Style Transfer Really Need?  
An Ablation Study  
(Supplementary Material)

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This supplementary file is to convince the readers that the results in the main paper is general to different combinations of content/style images. So we simply reproduce the original diagrams in the paper with different content and style images. Images are taken from [2].

References


Figure 1: Removing the content loss
Figure 2: Varying the biases while keeping trained weights.
Figure 3: Continuously or densely distributed weights
Figure 4: Symmetric discrete weights with fixed biases (0.5)
Figure 5: Removal of structure

Figure 6: Alternative first-layer convolution kernels
Figure 7: Using image pyramids instead of multi-layer nonlinearities
Figure 8: Removing the content loss
Figure 9: Varying the biases while keeping trained weights
Figure 10: Continuously or densely distributed weights
Figure 11: Symmetric discrete weights with fixed biases (0.5)
Figure 12: Removal of structure

Figure 13: Alternative first-layer convolution kernels
Figure 14: Using image pyramids instead of multi-layer nonlinearities
Figure 15: Removing the content loss
Figure 16: Varying the biases while keeping trained weights
Figure 17: Continuously or densely distributed weights
Figure 18: Symmetric discrete weights with fixed biases (0.5)
Figure 19: Removal of structure

Figure 20: Alternative first-layer convolution kernels
Figure 21: Using image pyramids instead of multi-layer nonlinearities
Figure 22: Removing the content loss
Figure 23: Varying the biases while keeping trained weights
Figure 24: Continuously or densely distributed weights
(a) Content image  (b) Style image  (c) Baseline  (d) Trained weights

(e) Uniform(−0.1, 0.1)  (f) {±0.1}  (g) {±0.1} trained binarized  (h) {±0.1, 0}

(i) {±0.1, 0, 0}  (j) {±0.2}  (k) {±0.4}  (l) {±0.4, ±0.2, ±0.1, 0}

Figure 25: Symmetric discrete weights with fixed biases (0.5)
Figure 26: Removal of structure

Figure 27: Alternative first-layer convolution kernels
Figure 28: Using image pyramids instead of multi-layer nonlinearities
Figure 29: Removing the content loss
Figure 30: Varing the biases while keeping trained weights
Figure 31: Continuously or densely distributed weights
Figure 32: Symmetric discrete weights with fixed biases (0.5)
Figure 33: Removal of structure

Figure 34: Alternative first-layer convolution kernels
Figure 35: Using image pyramids instead of multi-layer nonlinearities

(a) Gaussian pyramid without pooling  (b) Laplacian pyramid without pooling
(c) Gaussian pyramid with pooling  (d) Laplacian pyramid with pooling
Figure 36: Removing the content loss
Figure 37: Varying the biases while keeping trained weights
Figure 38: Continuously or densely distributed weights
Figure 39: Symmetric discrete weights with fixed biases (0.5)
Figure 40: Removal of structure

Figure 41: Alternative first-layer convolution kernels
Figure 42: Using image pyramids instead of multi-layer nonlinearities
Figure 43: Removing the content loss
Figure 44: Varying the biases while keeping trained weights
Figure 45: Continuously or densely distributed weights
Figure 46: Symmetric discrete weights with fixed biases (0.5)
Figure 47: Removal of structure

(a) Content image  
(b) Style image  
(c) Baseline  
(d) \{±0.1\}

(e) No ReLU no pooling no doubling  
(f) No ReLU  
(g) Neither pooling nor doubling (NPND)  
(h) With doubling but no pooling

(i) NPND, 4 filters  
(j) NPND, 16 filters  
(k) NPND, 71 filters  
(l) NPND, 512 filters

Figure 48: Alternative first-layer convolution kernels

(a) Basic set 1, strategy 4 (32-channel)  
(b) Basic set 2, strategy 1 (18-channel)  
(c) Basic set 3, strategy 3 (64-channel)  
(d) 2 × 2 kernels, random, 64-channel  
(e) 3 × 3 kernels, random, 64-channel
Figure 49: Using image pyramids instead of multi-layer nonlinearities.
Figure 50: Removing the content loss
Figure 51: Varying the biases while keeping trained weights
Figure 52: Continuously or densely distributed weights
Figure 53: Symmetric discrete weights with fixed biases (0.5)
Figure 54: Removal of structure

Figure 55: Alternative first-layer convolution kernels
Figure 56: Using image pyramids instead of multi-layer nonlinearities
Figure 57: Removing the content loss
Figure 58: Varying the biases while keeping trained weights
Figure 59: Continuously or densely distributed weights
Figure 60: Symmetric discrete weights with fixed biases (0.5)
Figure 61: Removal of structure

Figure 62: Alternative first-layer convolution kernels
Figure 63: Using image pyramids instead of multi-layer nonlinearities
Figure 64: Removing the content loss
Figure 65: Varying the biases while keeping trained weights
Figure 66: Continuously or densely distributed weights
(a) Content image  (b) Style image  (c) Baseline  (d) Trained weights

(e) Uniform(−0.1, 0.1)  (f) {±0.1}  (g) {±0.1} trained binaire  (h) {±0.1, 0}

(i) {±0.1, 0, 0}  (j) {±0.2}  (k) {±0.4}  (l) {±0.4, ±0.2, ±0.1, 0}

Figure 67: Symmetric discrete weights with fixed biases (0.5)
Figure 68: Removal of structure

Figure 69: Alternative first-layer convolution kernels
Figure 70: Using image pyramids instead of multi-layer nonlinearities.