# Unsupervised Learning of Artistic Styles with Archetypal Style Analysis

# Supplementary Material

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Here, we presents a set of additional results, which were not included in the paper for space limitation reasons, as well as experimental material such as the full set of archetypes learned by our approach.

## Contents



## 1 Influence of parameters $\gamma$, $\delta$ and comparison with [1].

In this section, we provide additional comparisons between our variant of [1] and the original one. All cases seem to confirm that (i) the heuristic $\gamma = \delta$ is reasonably good in terms of quality of the results, and (ii) our variant is much more accurate than [1] in terms of content preservation as soon as the amount of stylization is less than 100%. Figure 1 visualizes why the method of [1] loses so much detail regardless of the strength of stylization. Figures 2, 3, and 4 show more detailed comparisons of the two variants for different artworks and target styles.

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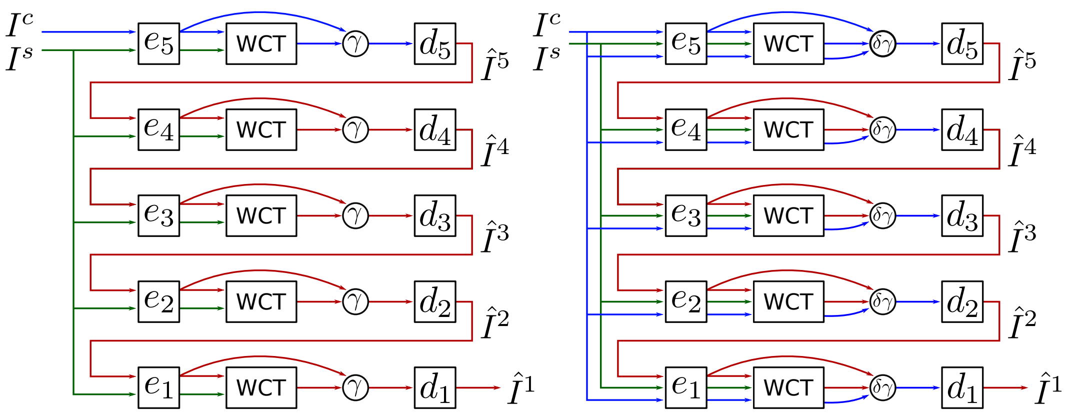



Figure 1: Left: In [1] the original content image is used only once. While style information is injected before every decoding step, information lost during the encoding, coloring and decoding steps can never be recovered. Right: Using $I^c$ at every layer allows the decoders to produce more faithful reconstructions if desired.

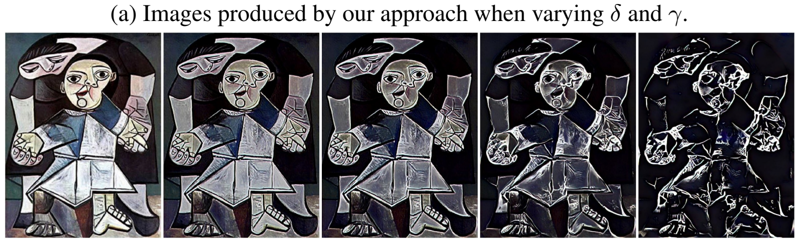

(a) Images produced by our approach when varying $\delta$ and $\gamma$.

(b) Images produced by our approach when $\gamma = \delta$, jointly increasing these parameters from 0 (left) to 1 (right).

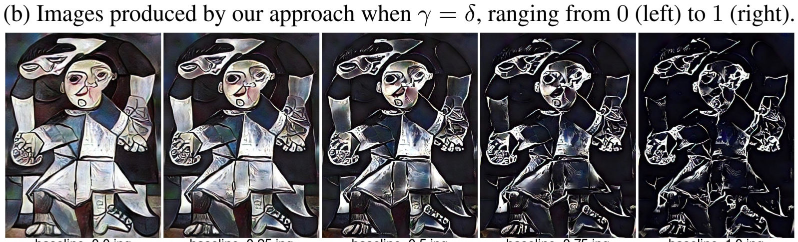

(c) Images produced by the original approach of [1] when changing their stylization parameter.

Figure 2: Comparison of stylization control between our approach and [1].


(a) Images produced by our approach when varying $\delta$ and $\gamma$.

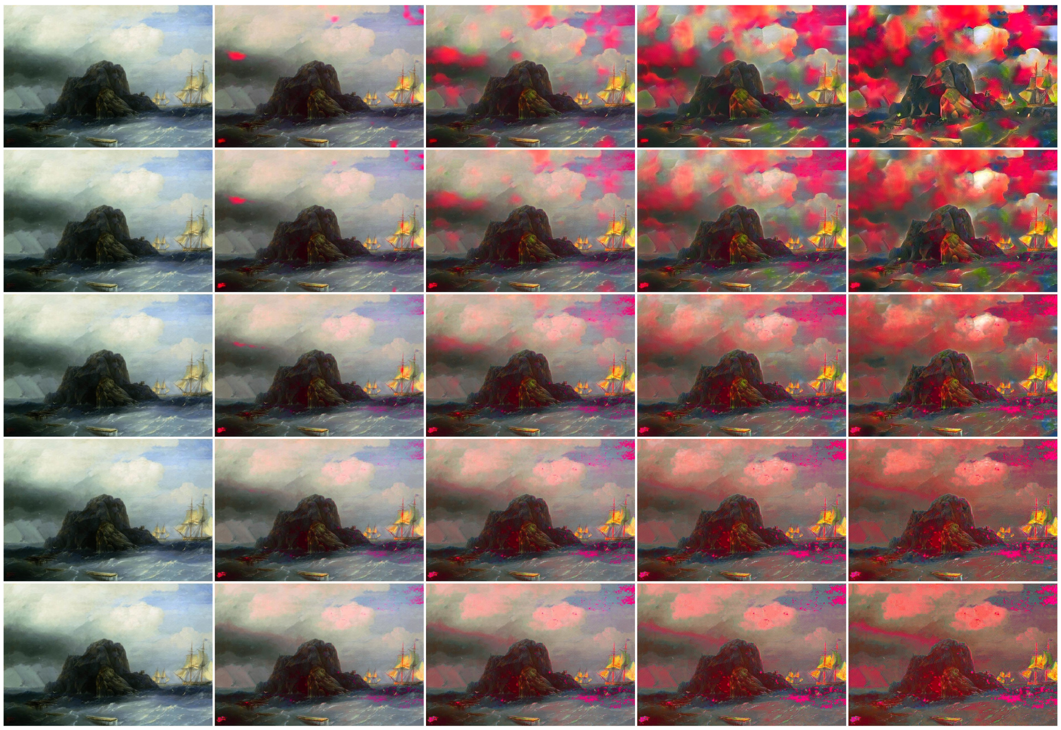


(b) Images produced by our approach when $\gamma = \delta$, ranging from $0$ (left) to $1$ (right).



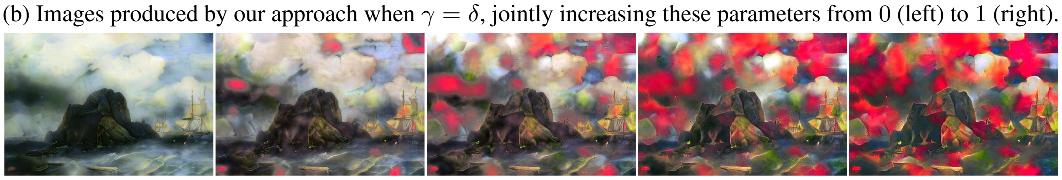

(c) Images produced by the original approach of [1].

Figure 3: Comparison of stylization control between our approach and [1].



(a) Images produced by our approach when varying $\delta$ and $\gamma$.

(b) Images produced by our approach when $\gamma = \delta$, jointly increasing these parameters from 0 (left) to 1 (right).

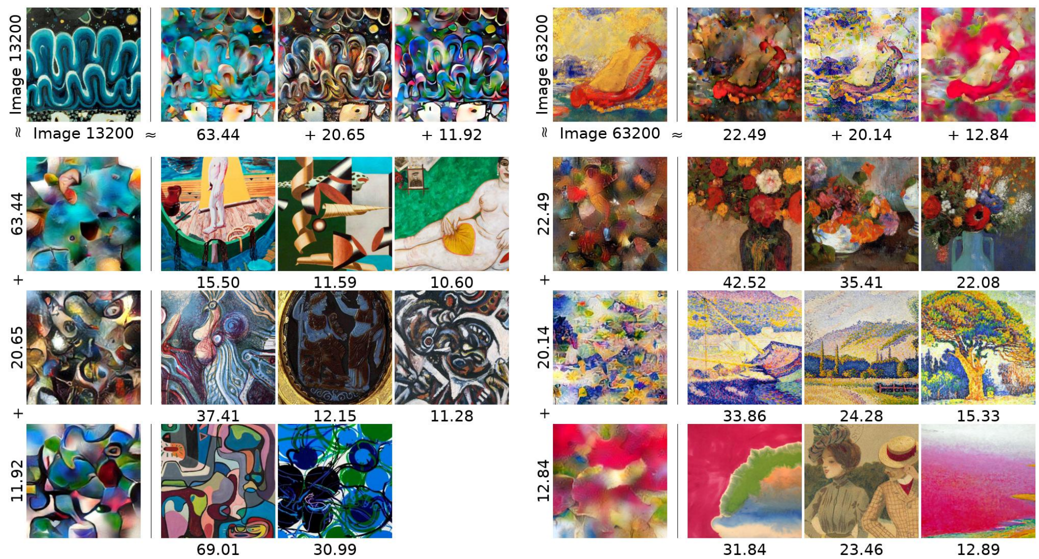


(c) Images produced by the original approach of [1] when changing their stylization parameter.

Figure 4: Comparison of stylization control between our approach and [1].

# 2 Examples of Image Decompositions

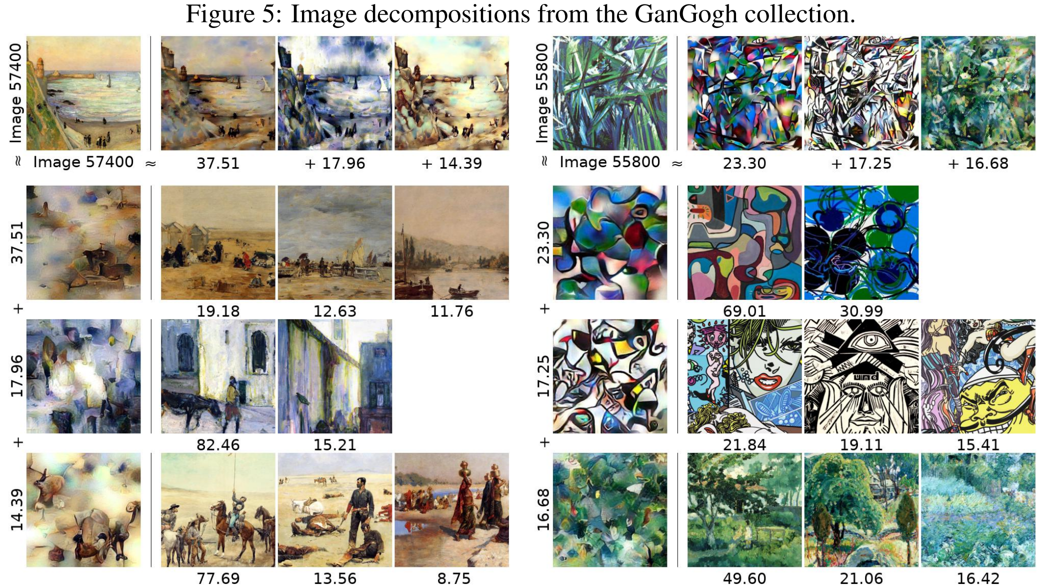
We show in this section a few additional image decompositions, involving trivial ones, meaningful ones, and failure cases.




(a)

(b) Image decomposition.

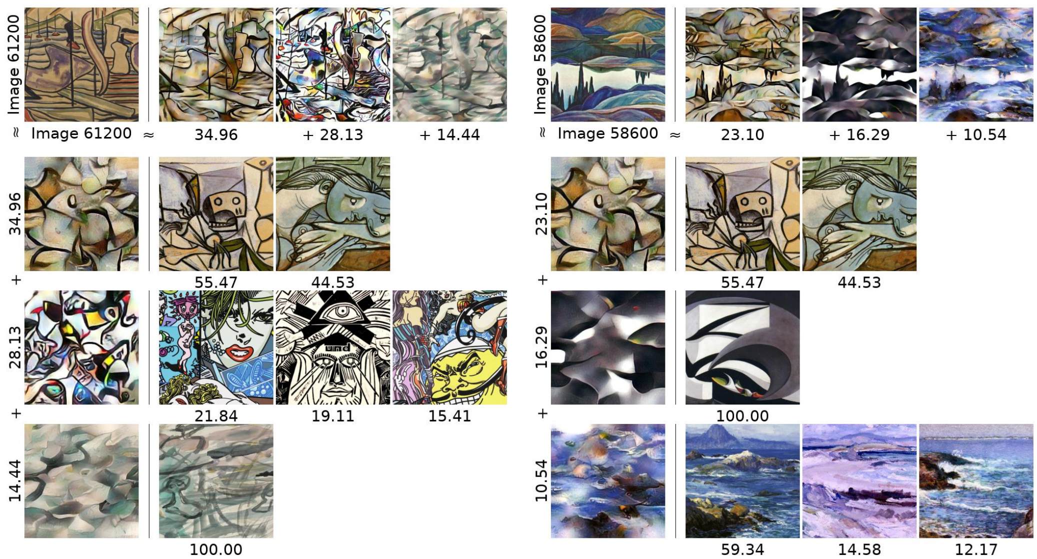
Figure 5: Image decompositions from the GanGogh collection.




(a)

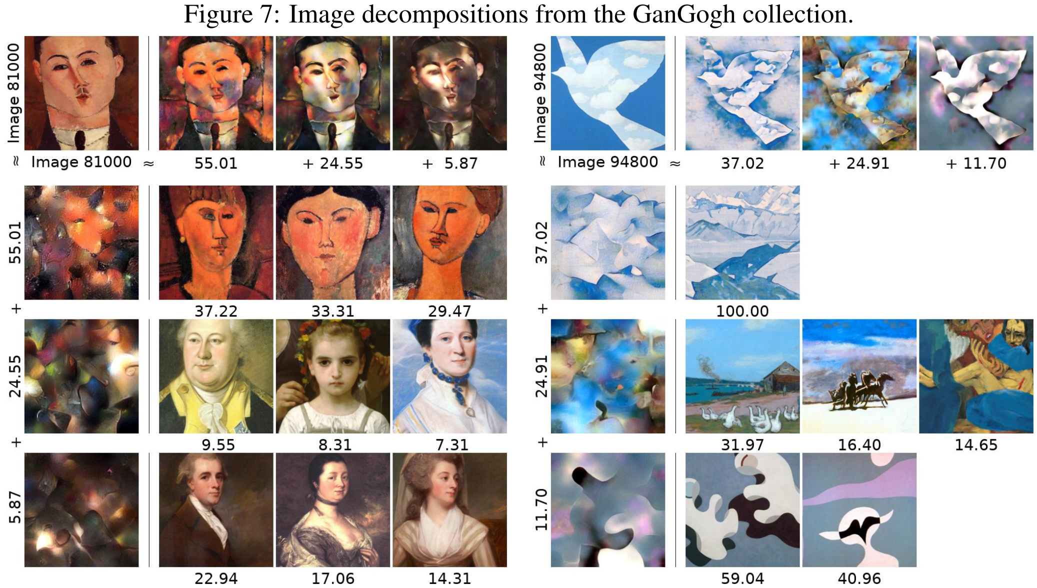
(b) Image decomposition.

Figure 6: Image decompositions from the GanGogh collection.



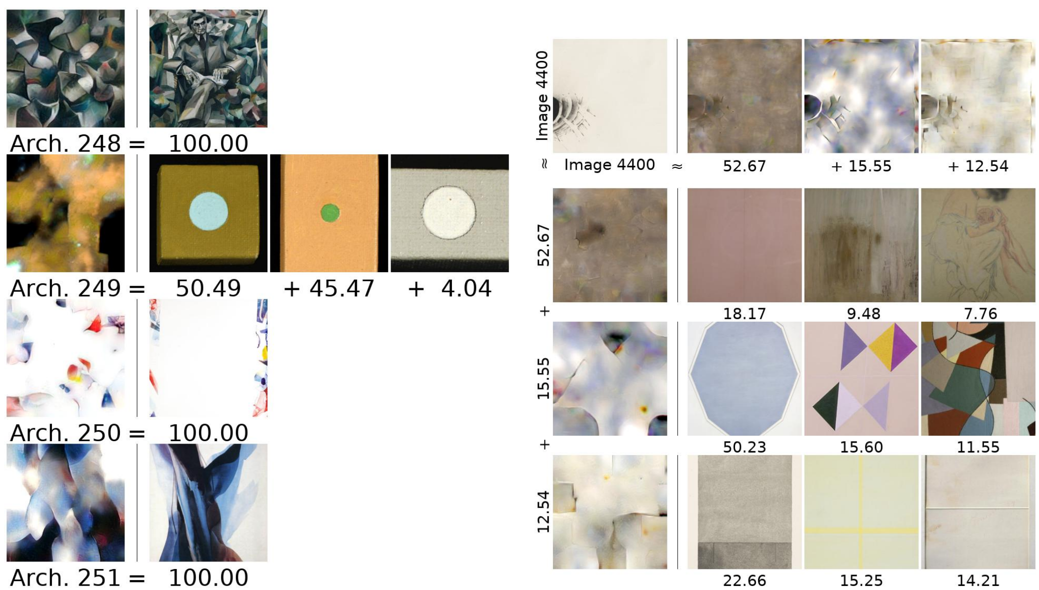

(a) (b) Image decomposition.

Figure 7: Image decompositions from the GanGogh collection.




(a) (b) Image decomposition.

Figure 8: Image decompositions from the GanGogh collection.




(a) Four archetypal decompositions.



(b) Image decomposition.

Figure 9: Failure cases of two archetypal decompositions (a) and image decomposition (b). (a): the second archetype seems to code only for "circle on rough canvas". While this is definitely the defining characteristic of the contributing images, it is not helpful for stylization. The other rows are examples of degenerate archetypes, *i.e.* archetypes with a single contribution. (b) A non-sparse image decomposition, hence difficult to interpret. The strongest three components seem to represent the absence of texture, but it is not clear what their contribution is to the image style.

# 3 Additional Examples of Style Manipulation

In this section, we present additional examples of style enhancement and interplation, as well as examples of stylization of natural photographs.

(a) “Woman with Book” by Pablo Picasso. From the GanGogh collection.

Figure 10: We demonstrate the enhancement of the two most prominent archetypal styles for different artworks. The middle panel shows a near-perfect reconstruction of the original content image in every case and uses parameters $\gamma, \delta = 0.5$. Then, we increase the relative weight of the strongest component towards the left, and of the second component towards the right. Simultaneously, we increase $\gamma$ and $\delta$ from $0.5$ in the middle panel to $0.95$ on the outside.

Figure 11: “Maria and Baby” by Robert Henri. Free archetypal combination.

Figure 12: Tübingen image

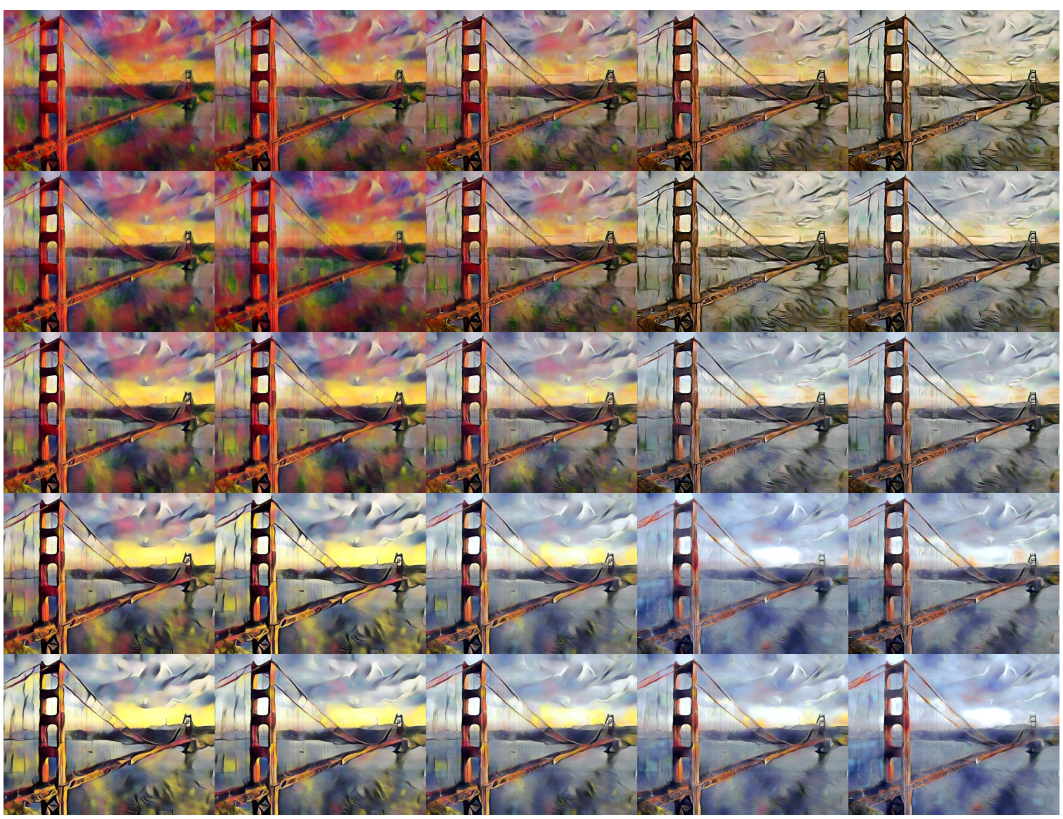


Figure 13: Golden Gate Bridge

Figure 14: Additional examples of style enhancements of van Gogh's works.

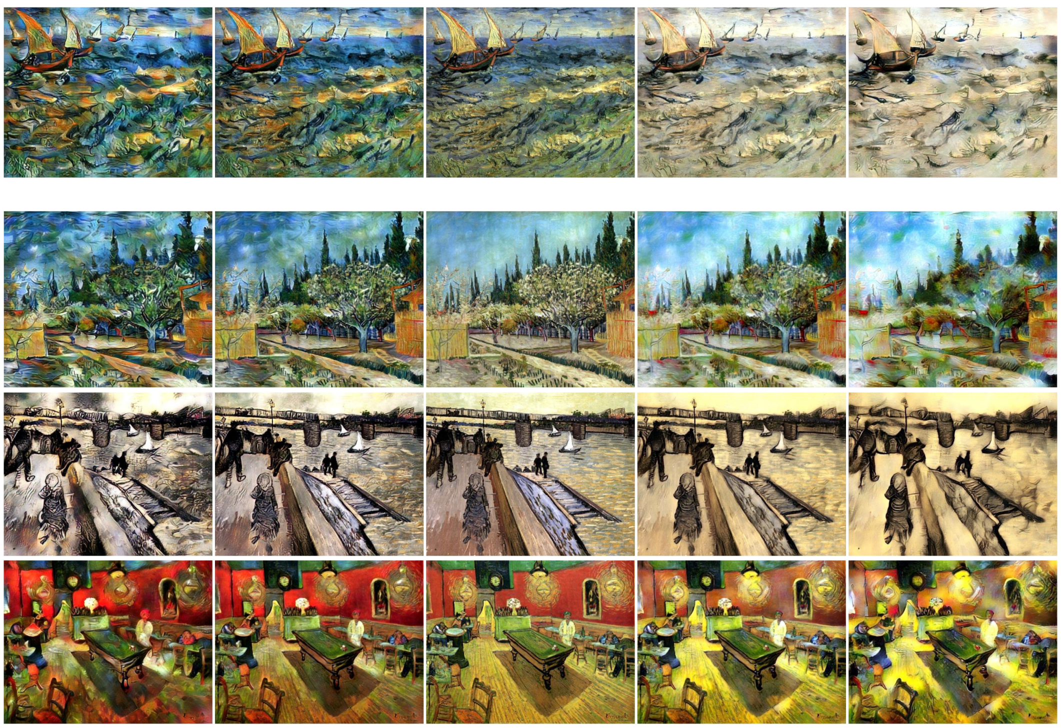
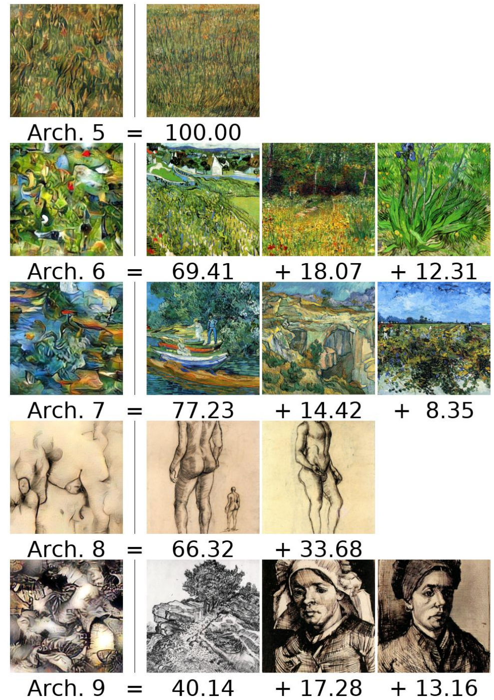


Figure 15: Additional examples of style enhancements of van Gogh's works.

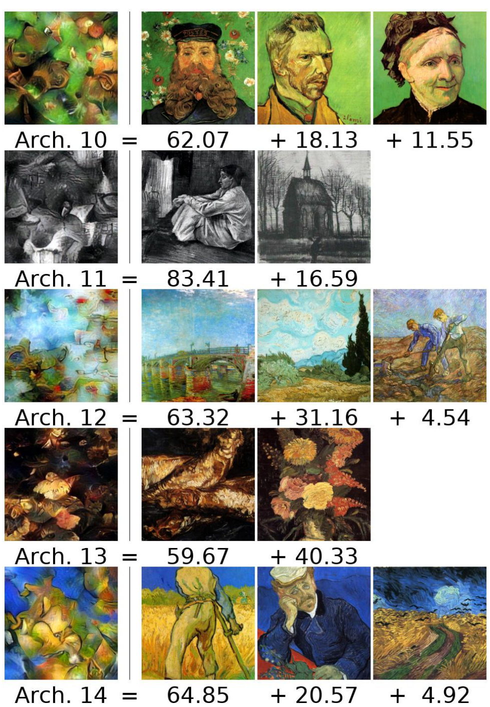
## 4 Full Set of van Gogh's Archetypes

In this section, we present the $k = 32$ archetypes learned on the collection of Van Gogh's paintings; the archetypes seem to cover van Gogh's artistic development relatively accurately. The full set of archetypes is shown in Figures 16 and 17.

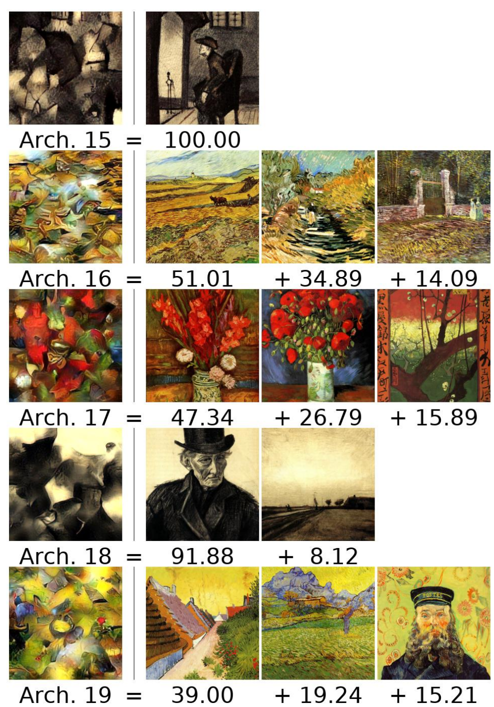

(a) Archetypes 0 to 4




(b) Archetypes 5 to 9

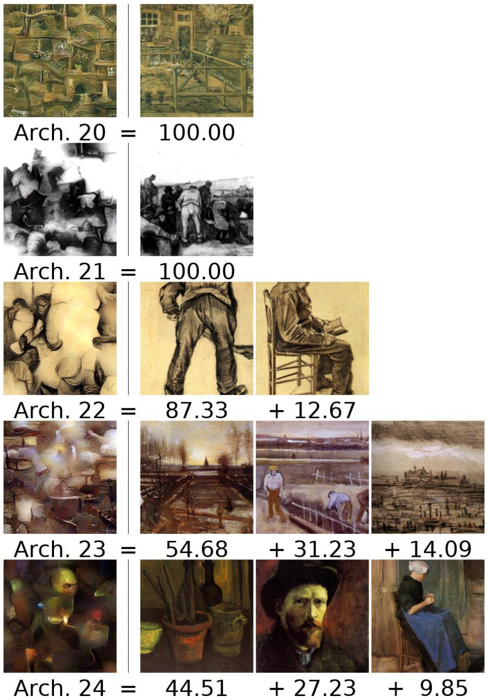



(c) Archetypes 10 to 14

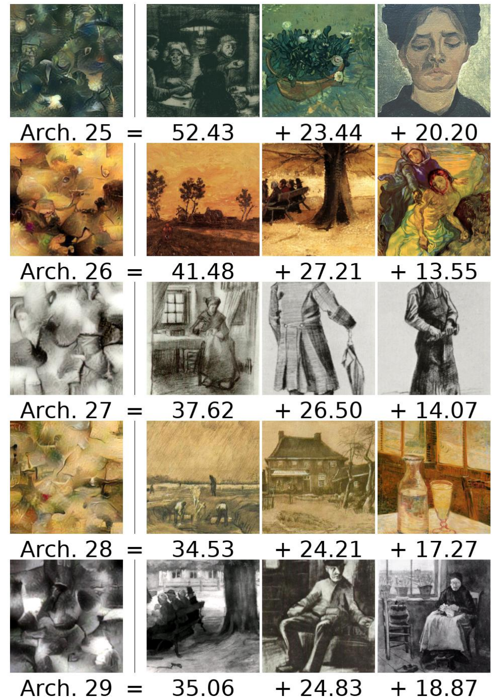



(d) Archetypes 15 to 19

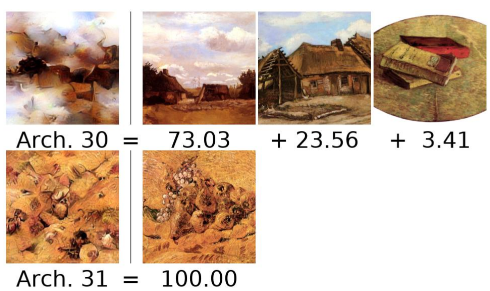
Figure 16: Archetypes 0 to 19




(a) Archetypes 20 to 24




(b) Archetypes 25 to 29

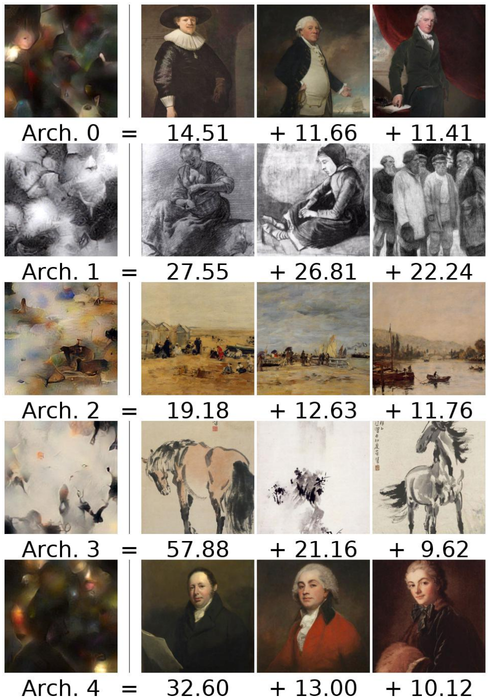



(c) Archetypes 30 to 31

Figure 17: Archetypes 20 to 31

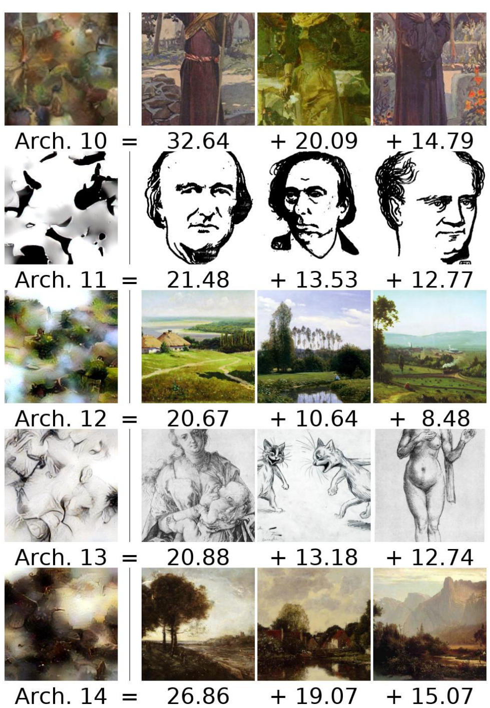
## 5 Full Set of GanGogh Archetypes

In this section, we provide the full set of $256$ archetypes learned on the Gangogh collection. Visualization is performed in the same way as in the main paper.

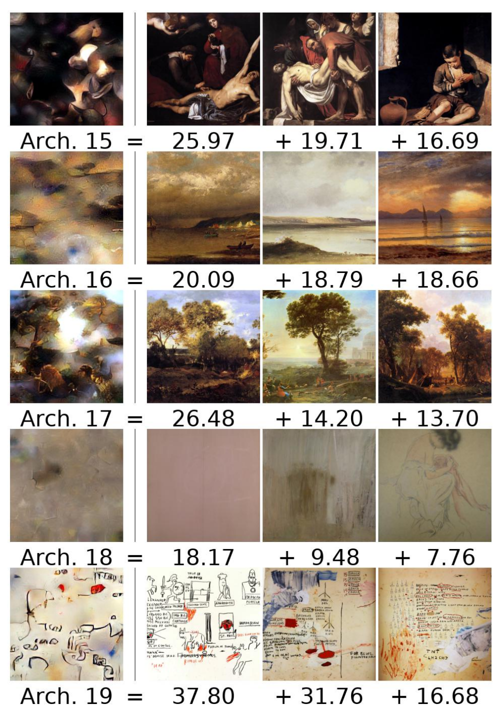



(a) Archetypes 0 to 4


(b) Archetypes 5 to 9

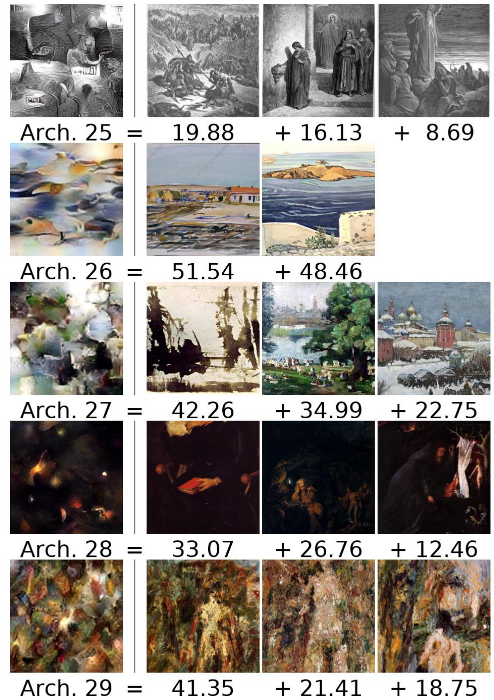



(c) Archetypes 10 to 14

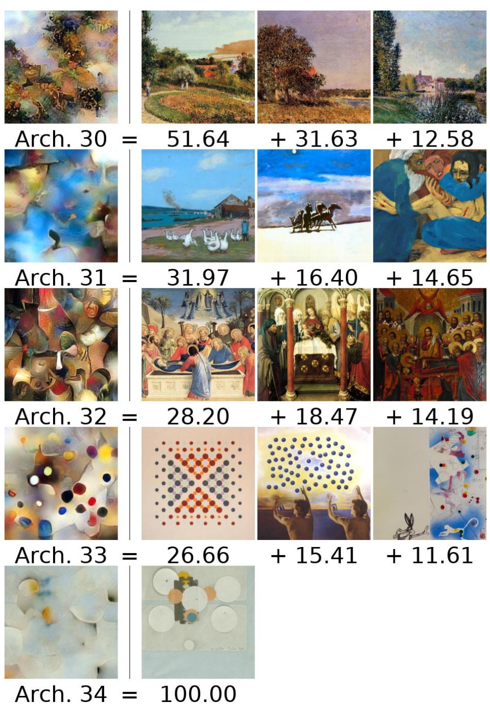



(d) Archetypes 15 to 19

(a) Archetypes 20 to 24

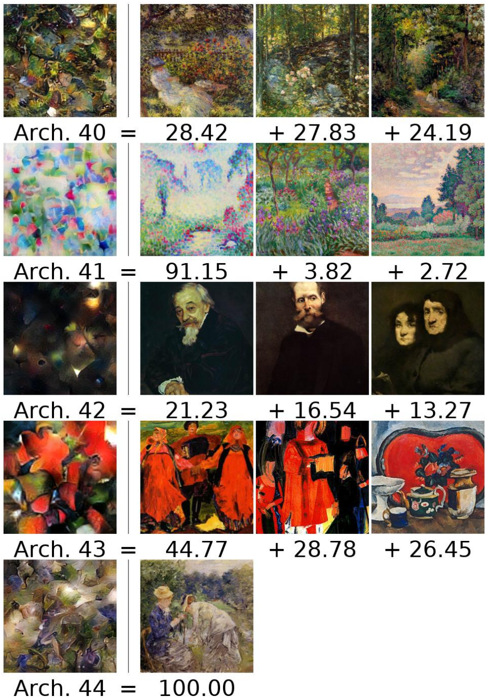


(b) Archetypes 25 to 29

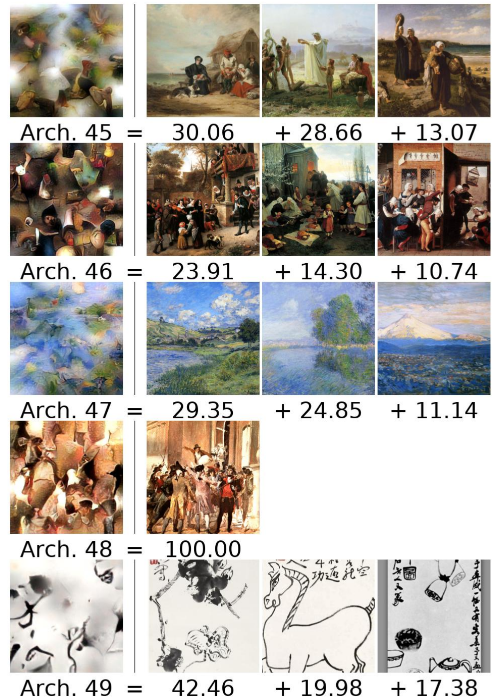


(c) Archetypes 30 to 34

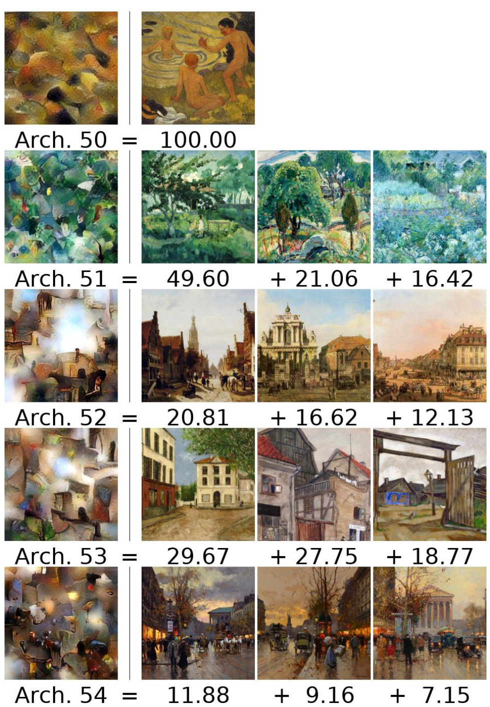
(d) Archetypes 35 to 39



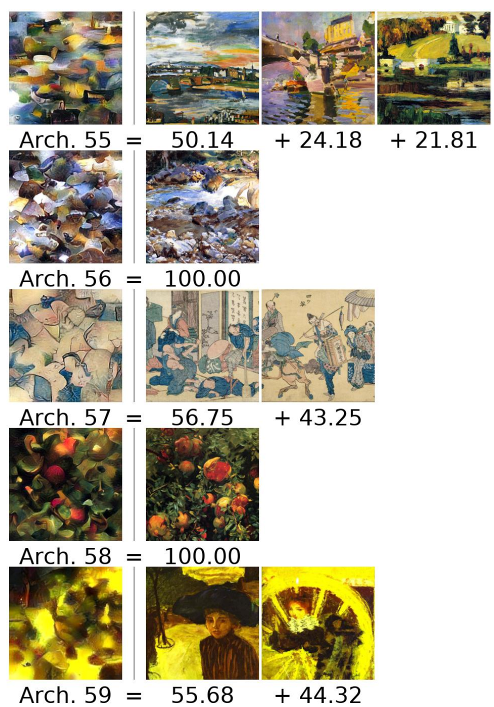

(a) Archetypes 40 to 44



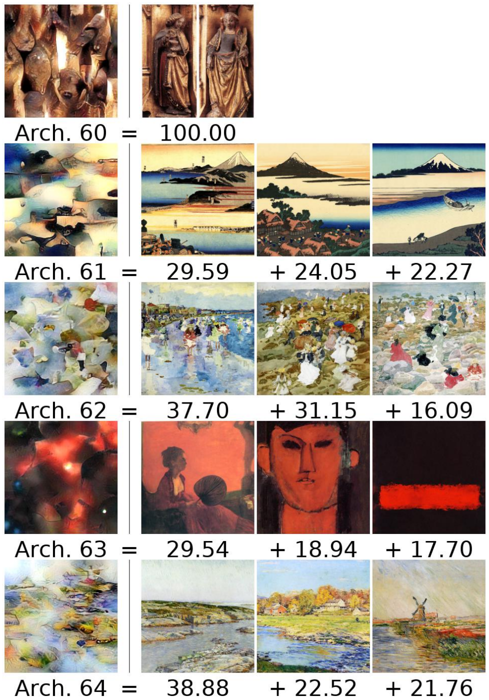

(b) Archetypes 45 to 49



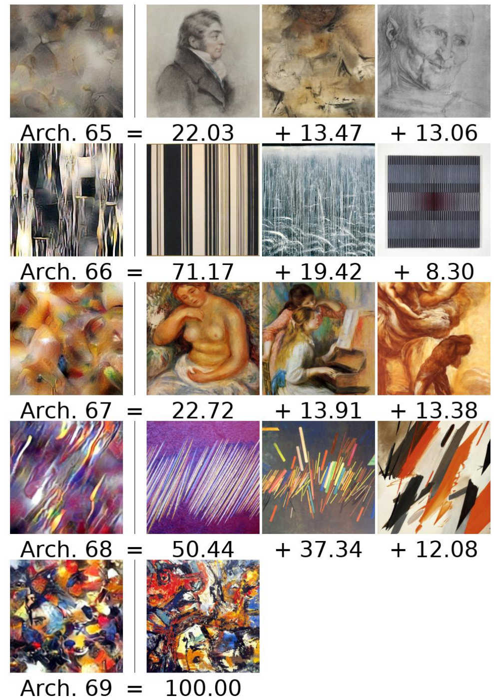

(c) Archetypes 50 to 54



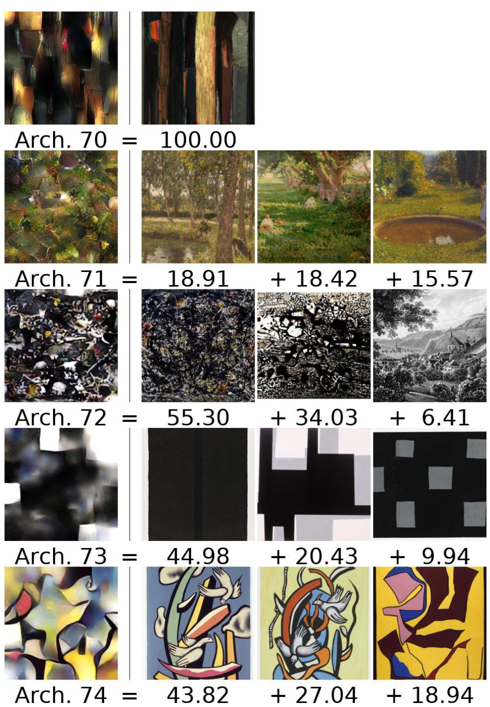

(d) Archetypes 55 to 59



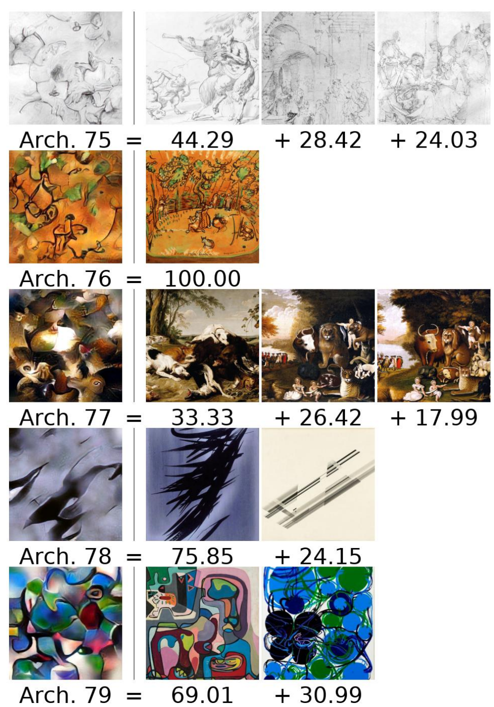

(a) Archetypes 60 to 64



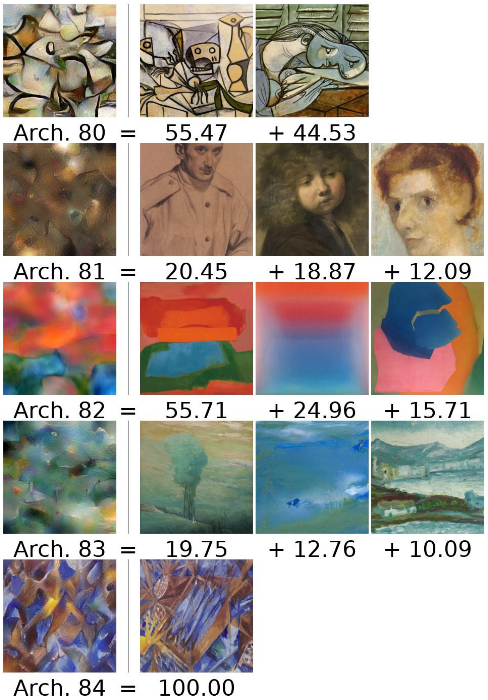

(b) Archetypes 65 to 69



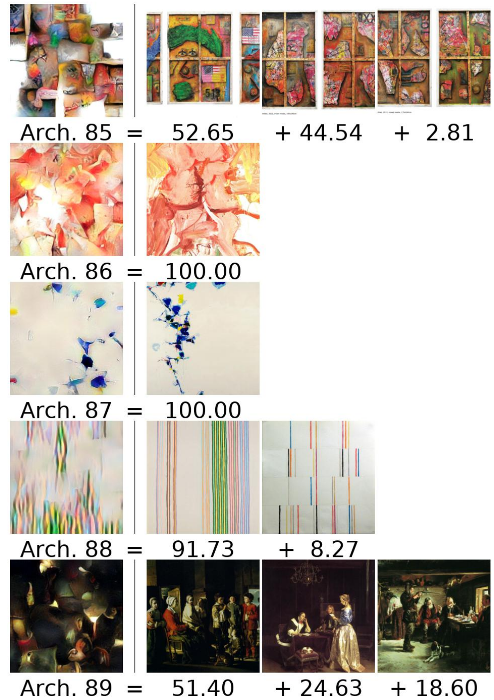

(c) Archetypes 70 to 74




(d) Archetypes 75 to 79




(a) Archetypes 80 to 84

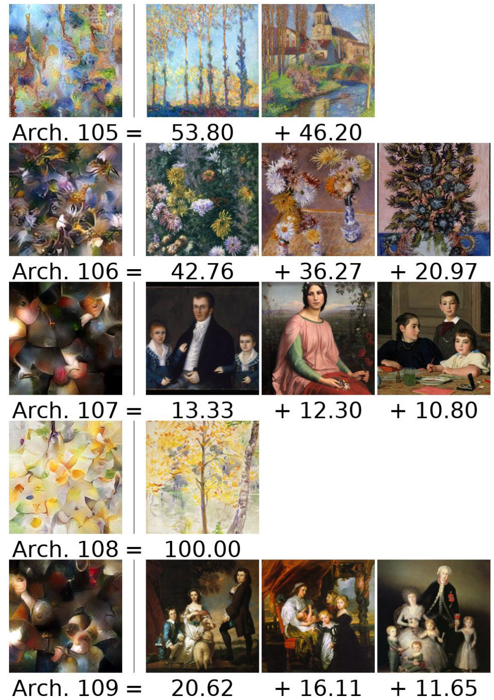



(b) Archetypes 85 to 89

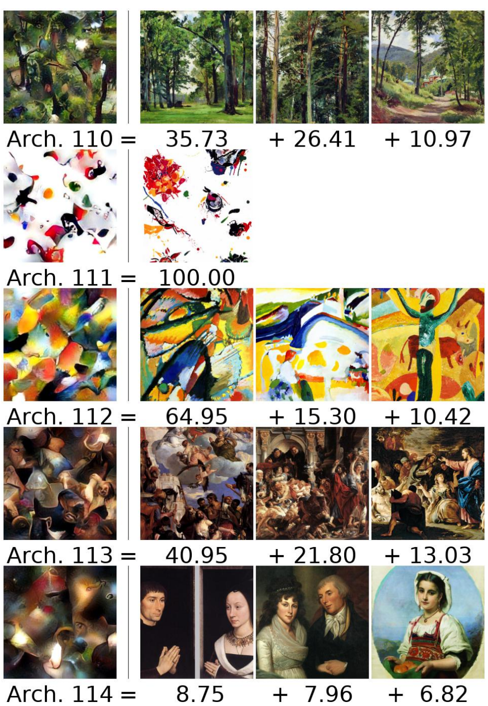

(c) Archetypes 90 to 94


(d) Archetypes 95 to 99

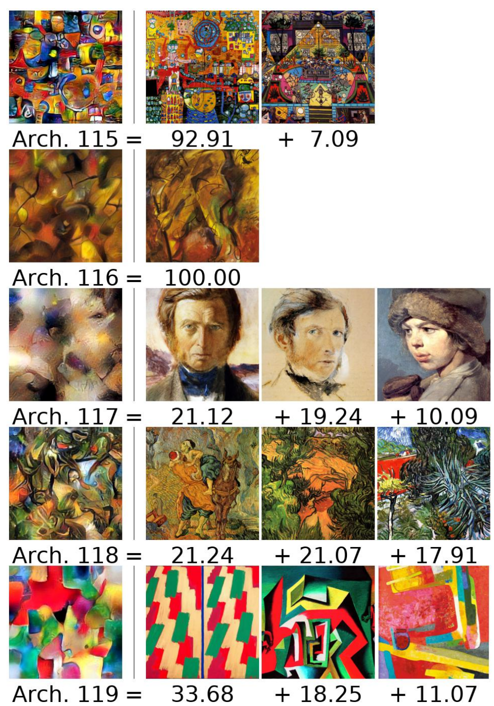

(a) Archetypes 100 to 104




(b) Archetypes 105 to 109



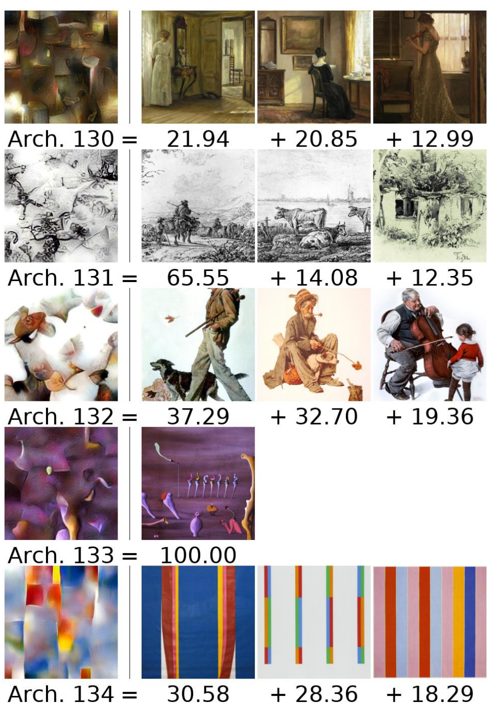

(c) Archetypes 110 to 114



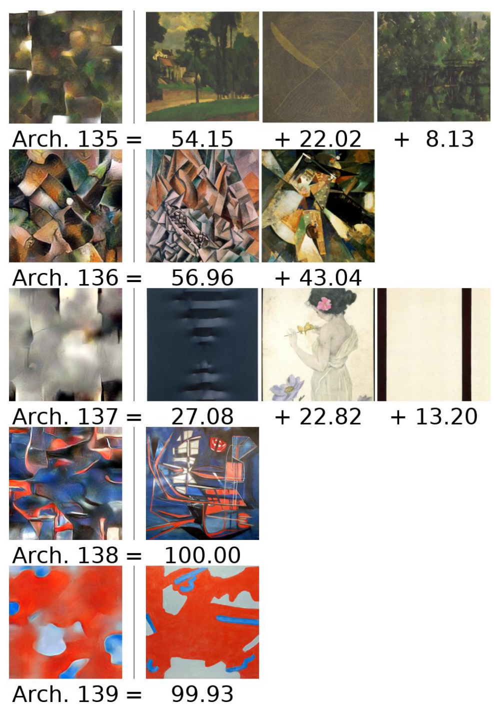

(d) Archetypes 115 to 119


(a) Archetypes 120 to 124

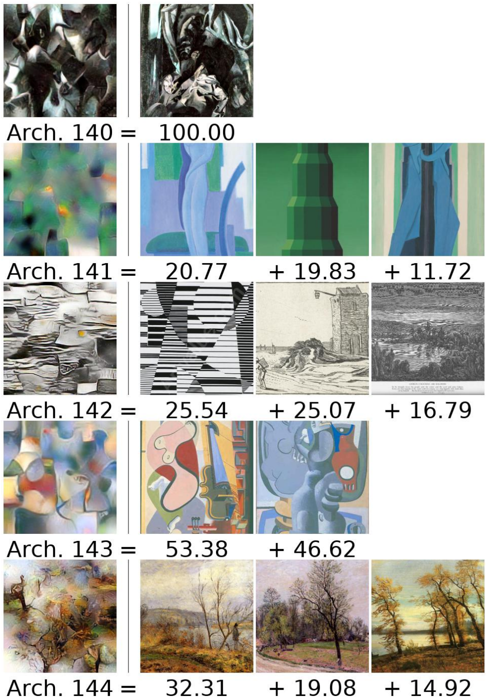

(b) Archetypes 125 to 129




(c) Archetypes 130 to 134

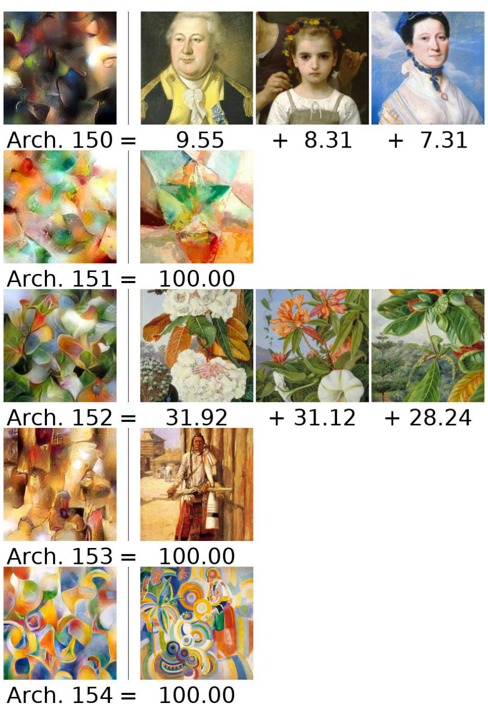



(d) Archetypes 135 to 139




(a) Archetypes 140 to 144


(b) Archetypes 145 to 149

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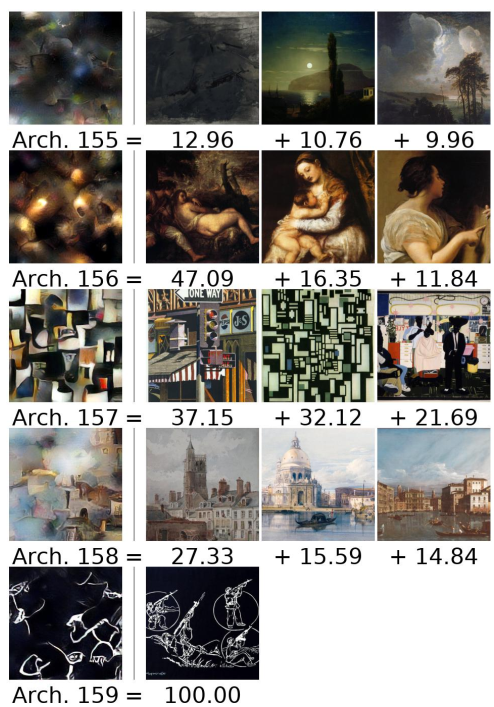


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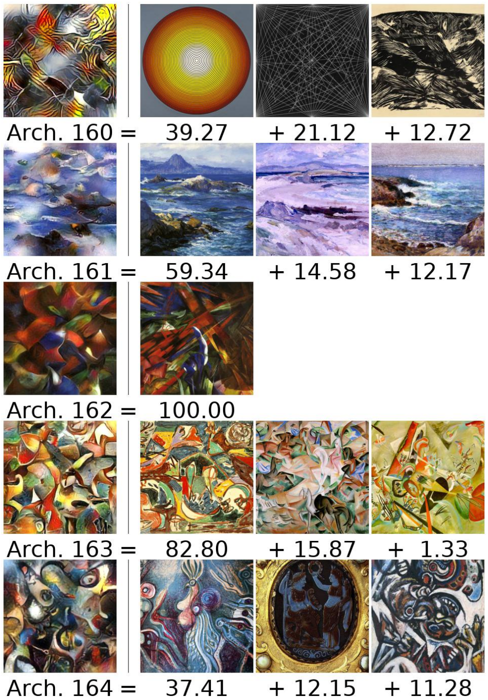
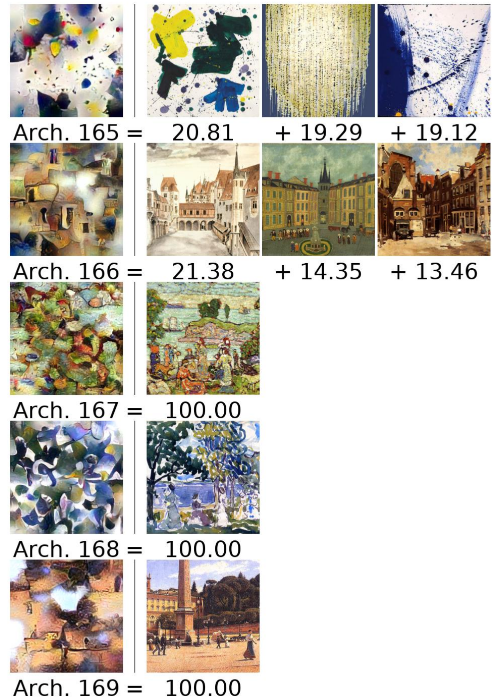



(a) Archetypes 160 to 164

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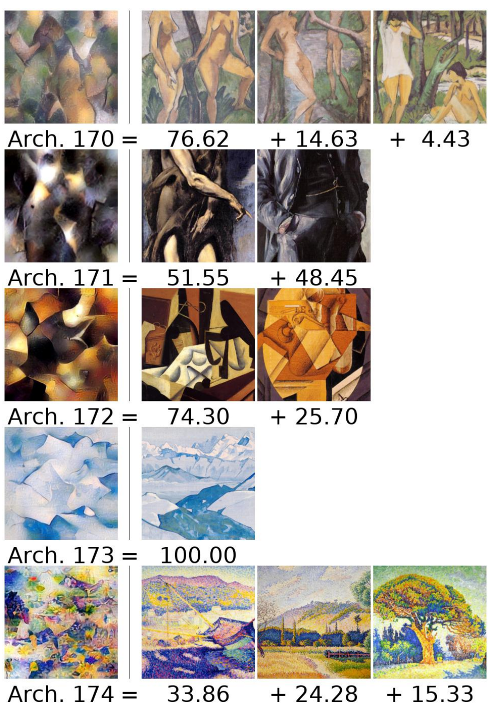
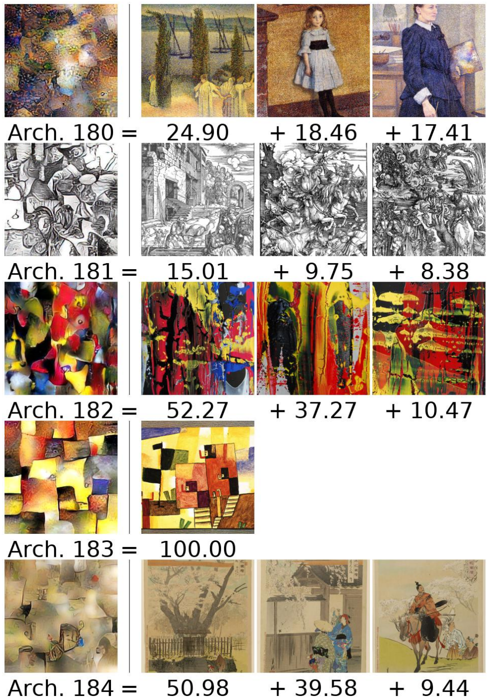
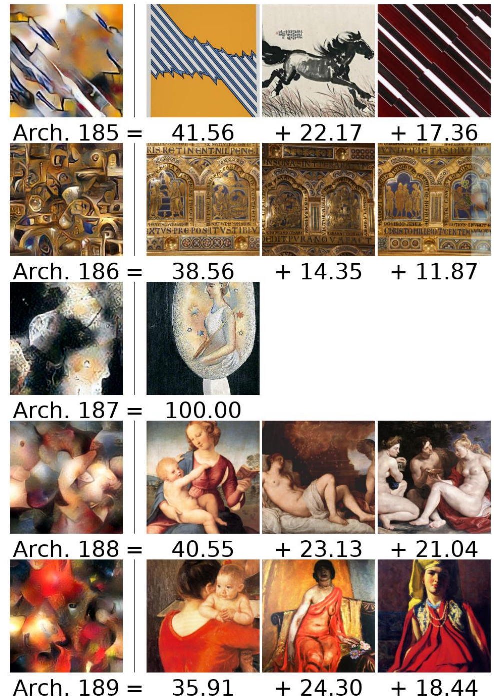



(c) Archetypes 170 to 174

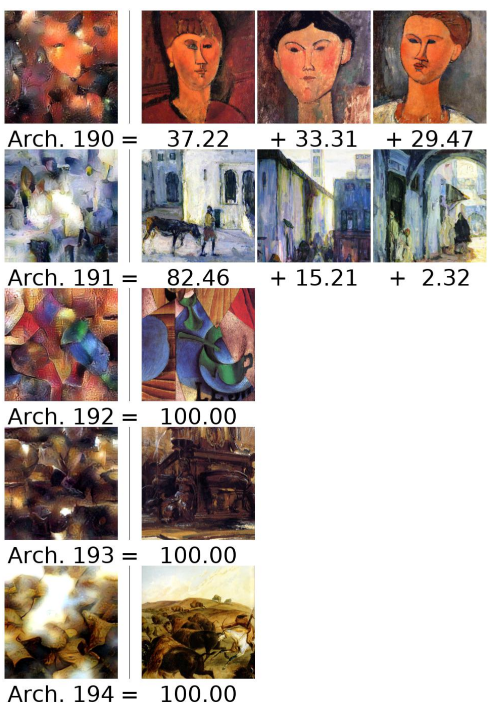

(d) Archetypes 175 to 179



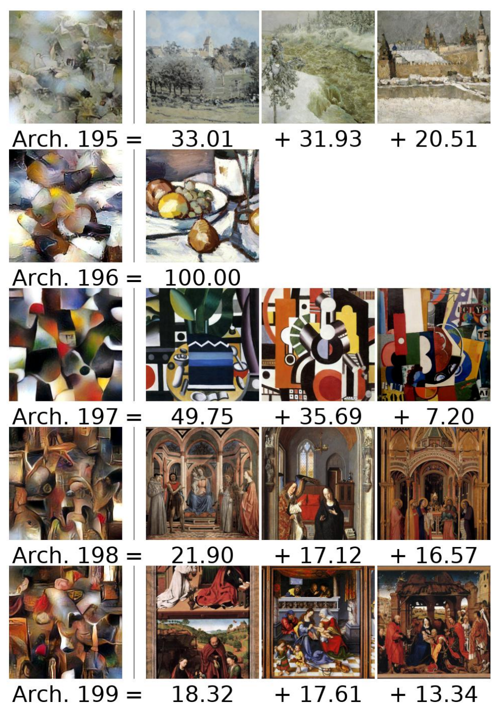
(a) Archetypes 180 to 184



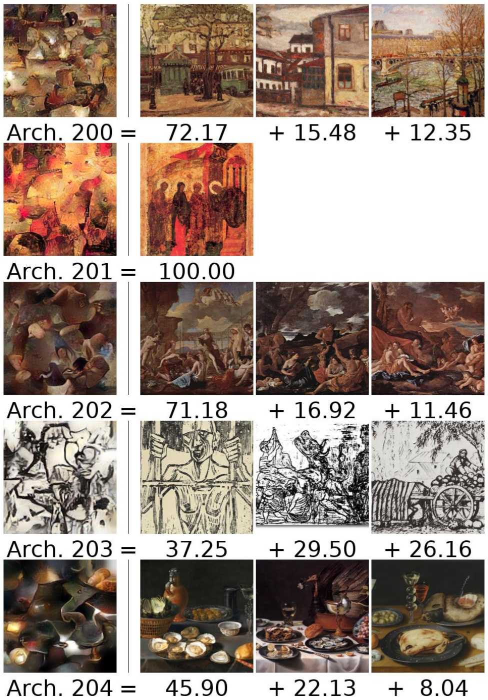
(b) Archetypes 185 to 189



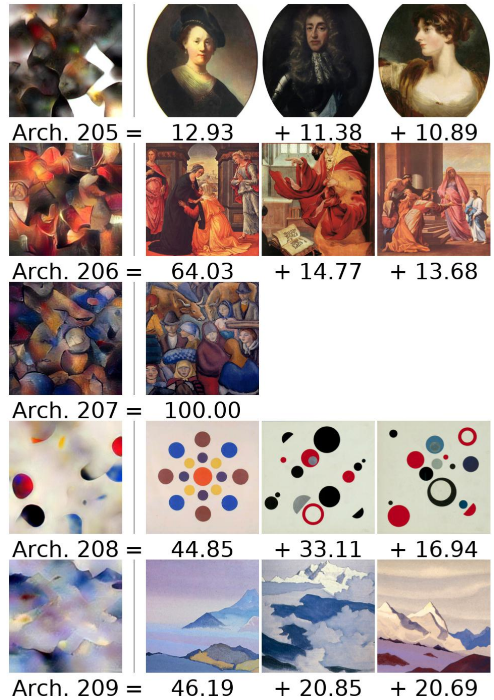
(c) Archetypes 190 to 194



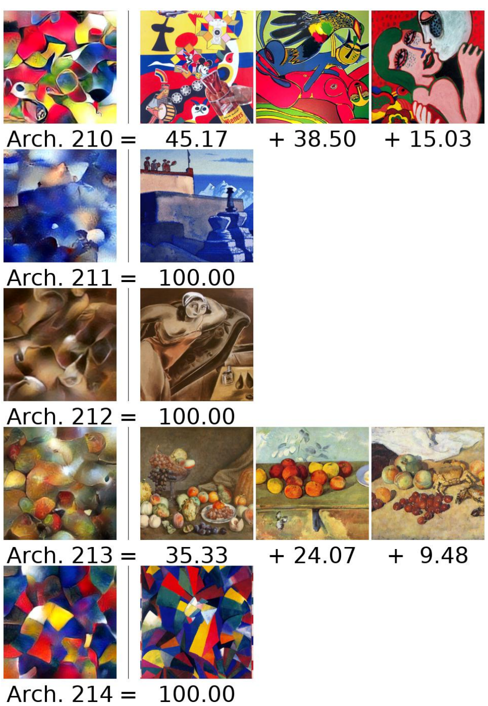
(d) Archetypes 195 to 199



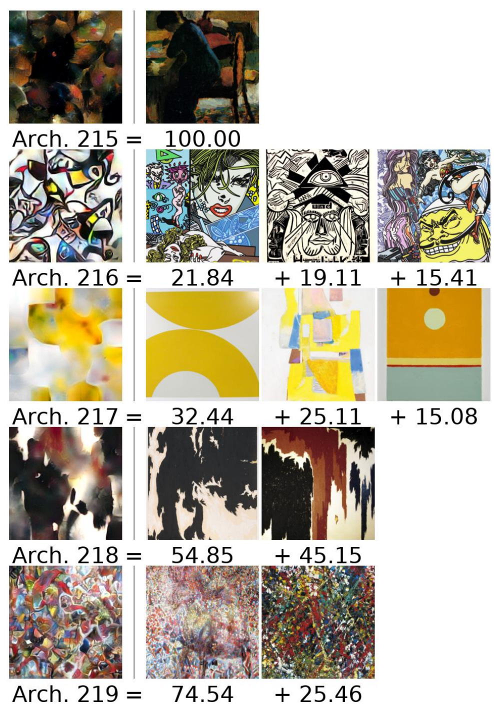
(a) Archetypes 200 to 204



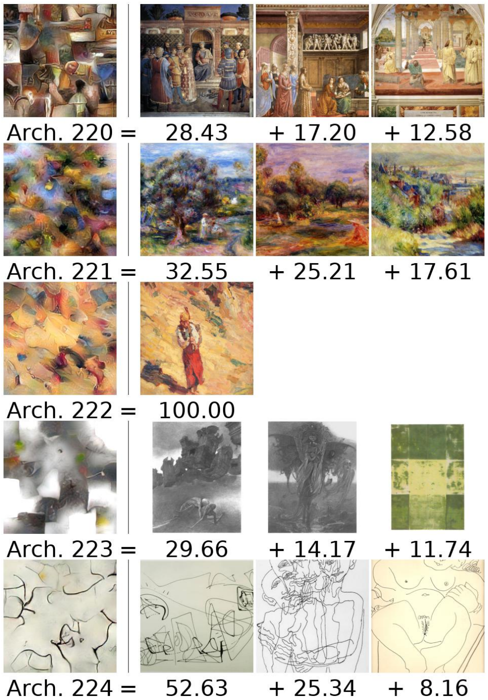
(b) Archetypes 205 to 209



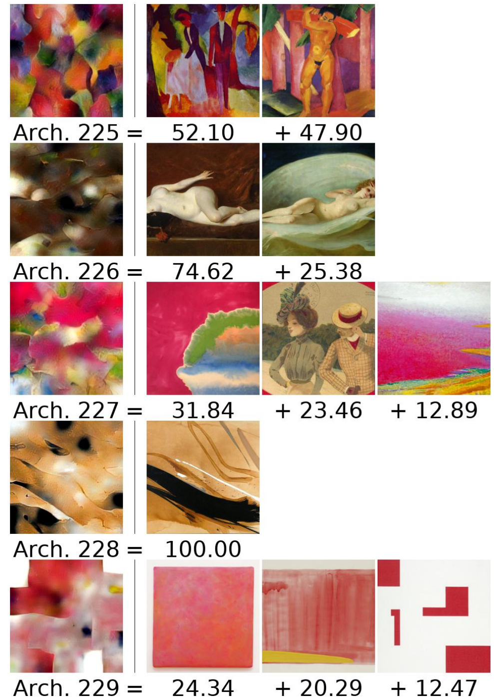
(c) Archetypes 210 to 214



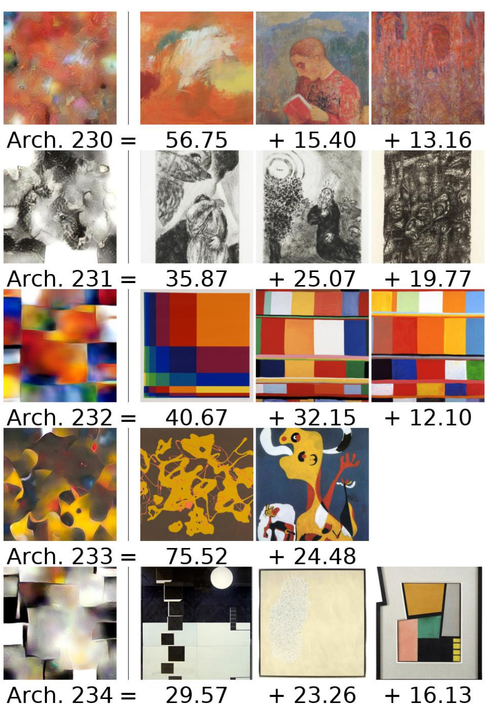
(d) Archetypes 215 to 219



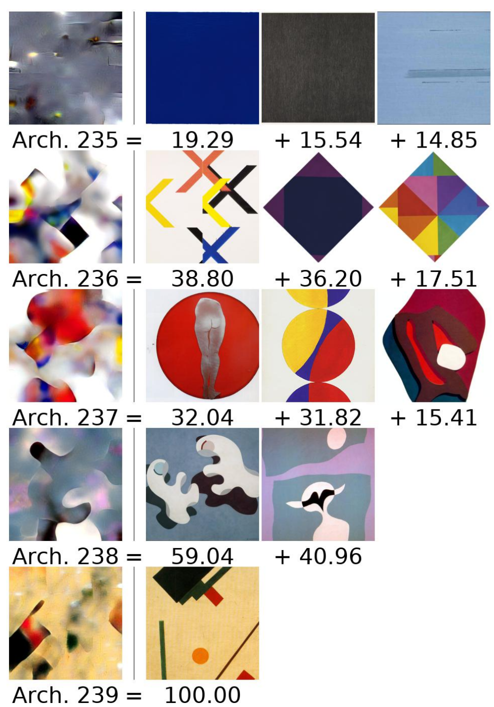

(a) Archetypes 220 to 224



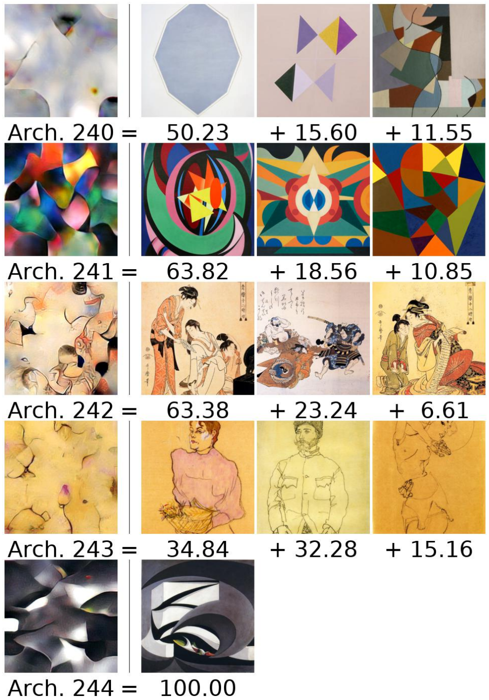

(b) Archetypes 225 to 229




(c) Archetypes 230 to 234

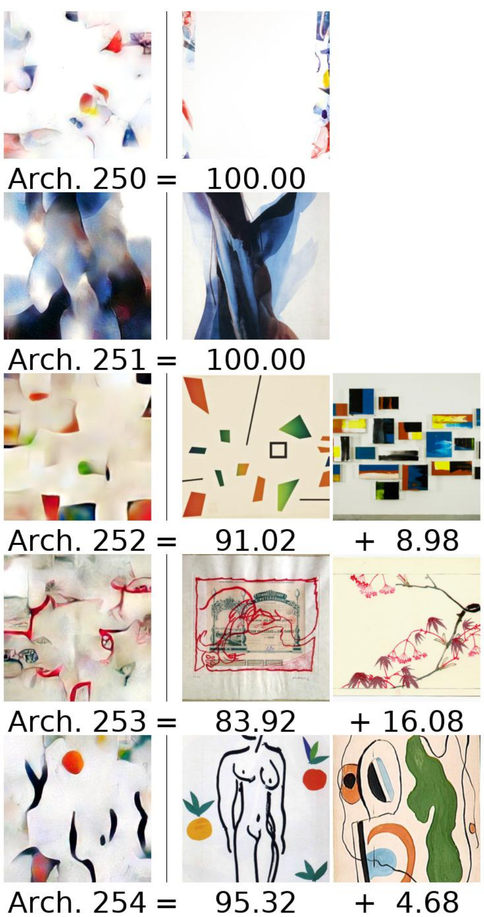



(d) Archetypes 235 to 239




(a) Archetypes 240 to 244


(b) Archetypes 245 to 249




(c) Archetypes 250 to 254


(d) Archetypes 255 to 255

# References

[1] Y. Li, C. Fang, J. Yang, Z. Wang, X. Lu, and M.-H. Yang. Universal style transfer via feature transforms. In *Adv. Neural Information Processing Systems (NIPS)*, 2017.