Fusing animal images using deep learning

1 Description

Adversarial Networks [1], Variational Autoencoders [2] and other generative DNNs allow to learn generative models able to reproduce distributions. They have been successfully applied to create artificial images that resemble real images. Convolutional neural networks [3, 4, 5, 6, 7] have been also applied to manipulate artistic images. For example, they have been used for style transfer [8, 9, 10, 11] or image translation [12, 13].

2 Objectives

Chimeras are mythical animals formed from parts of various animals. The goal of this project is to design and implement a deep learning approach (any of those mentioned in the previous section) for naturally fusing images of different animals (e.g., cats and horses) to create a "chimera".

The student should: 1) Select an appropriate DNN architecture. 2) Select convenient image datasets. 3) Implement the learning procedure that produces as output the fused images. 4) Although the evaluation of this project will be based on the quality of the images produced, a metric to evaluate whether the images are actually the fusion of the two animals can be also implemented.

As in other projects, a report should describe the characteristics of the design, implementation, and results. A Jupyter notebook should include calls to the implemented function that illustrate the way it works.

3 Suggestions

- Read the relevant bibliography about style transfer and image translation [8, 9, 10, 11, 12, 13].
- Implementations can use any Python library that implements DNNs.

References

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