Nearest Neighbor Classification for Classical Image Upscaling

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INTRODUCTION AND AIM

Given a set of ordered pixel data in the form of an image, our goal is to perform *upsampling* on the data such that:

- the resulting resolution is improved by some factor,
- the final result passes the "human test," having added new, believable, and realistic information and detail to the image,
- the time complexity for upscaling is relatively close to that of lossy upscaling implementations, and
- the process of upscaling does not require prior information, (*a classical approach*).

The existence of a method satisfying the following criteria implies that a more practical *and* time/space-efficient approach exists for the problem of lossy image upscaling, which we aim to prove through Nearest Neighbor Classification of pixels.

Our research is in collaboration with Mark Bauer and Quinn Ouyang as they pursue a learning-based approach to the same problem. As a whole, our teams aim to compare and contrast classical and learning-based approaches to upscaling by visual conformity and time and space complexity.

METRICS

Beginning with a set of images, we create a cascade of progressively smaller-resolution images for each image in the set. We then apply our algorithms to upsample back into their original sizes. Finally, we apply various metrics to measure similarity between the originals and reconstructions. Such metrics include: raw pixel comparison, MSE, RMSE, MAE, PSNR, and SSIM.

- MSE, RMSE, and MAE all deal with raw pixel comparison, and may not align well with human perception.
- PSNR measures the ratio between image values and the power of corrupting noise, while SSIM measures differences in structure, texture, and luminance. These metrics may align better with human perception.

By leveraging multiple metrics, we gain various perspectives and insights into the nature of differences between original images and reconstructions, providing means to better visualize the strengths and weaknesses of our approaches.

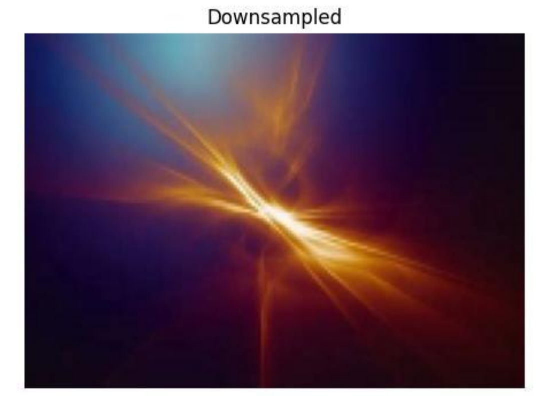
METHODS

KNN Interpolation

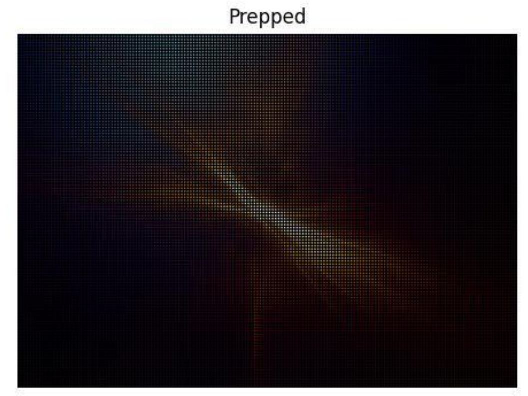
Our baseline is the simplest approach to solve the problem of image upsampling - filling in new pixels with the average of its K-nearest neighboring pixel values. Additionally for this approach, we support only fixed aspect-ratios between original and upscaled images, which equates the baseline functionality to "deblurring" an image.

Original

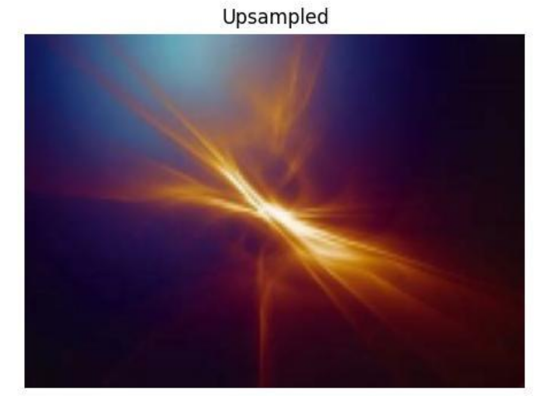
Downsampled



Prepped



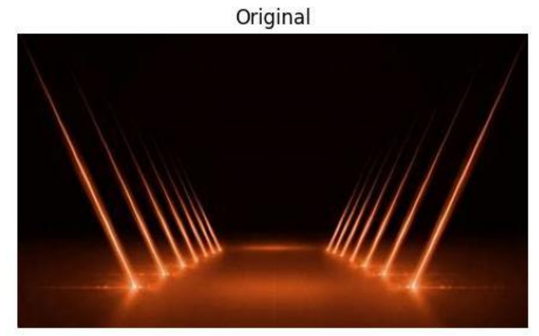
Upsampled



Upscaling for Dynamic Aspect Ratios

Our first expansion allows upscaling to aspect ratios differing from that of the original image, bringing new challenges and opportunities. For example, when upscaling one dimension while leaving the other unchanged, it would make sense to interpolate using pixels only along the changing dimension, rather than considering the true K-neighborhood as the baseline does.

Original



Upsampled

RESULTS

KNN Interpolation

For its relative simplicity, the baseline approach yielded decent results with minimal undesirable artifacts. Pitfalls of this approach were most visible surrounding detailed regions of crisp color change, such as borders between objects, where this naive approach produced grainy transitions not present in the original image. Additionally, since this approach must perform a KNN average for every new pixel, runtime increases exponentially with output size.

Original

Upsampled

Dynamic Aspect Ratios

We were able to add the functionality that allows for simple dynamic aspect ratio upscaling simply by generalizing our baseline code. In the case of single-dimensional upscaling, the algorithm can be easily modified to consider only pixels along the dimension in question during interpolation. When upscaling both dimensions by different factors, however, more complexity must be introduced to maintain this selective behavior. This is still an active area of experimentation.

Original

Upsampled

Original

Upsampled

FUTURE WORK

Selective Upscaling

In effort to improve the issue of time complexity, we envision selective upscaling. Leveraging color-gradients across the image, we will identify regions where pixel values remain constant; within these regions, interpolation during upsampling is unnecessary and wasteful. For example, in images with constant-color backgrounds, this implementation could skip a majority of pixel computations the baseline would endure. A core question in this expansion revolves around finding a balance between the added computation needed and the computational cost saved that benefits the widest variety of images.

Upscaling Convergence

To ensure that generated pixel data maintains the integrity of images, we will repeat our upscaling processes multiple times. We will use this method to find if any images converge to unrecognizable or poor quality data compared to the original images.

CONCLUSIONS

By delving into a classical approach for image upscaling, we intend to show that data generation without prior knowledge can match machine learning models. We believe that such a result, even at a relatively small difference in accuracy, will provide a few benefits: a massive decrease in storage costs for upscaling tools, an added "robustness" in terms of what images are upscaled, and a potential decrease in the computation time for the upscaled image.

ACKNOWLEDGEMENTS

We would like to personally thank Dr. Paris Smaragdis for providing us the opportunity to pursue this research endeavor, as well as Mark Bauer and Quinn Ouyang for their collaboration in the topic of image upscaling.

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