Image Reconstruction by Generative Adversarial Networks

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INTRODUCTION

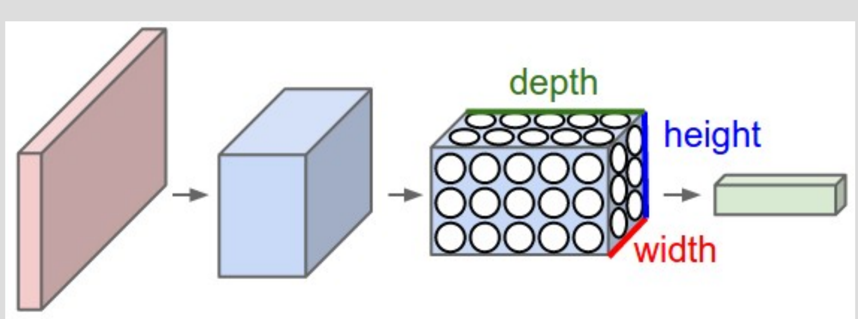
Given a photographic image with a portion cropped out, can a network be trained that can accurately fill in the gap to a realistic standard?

We explore the different methods of recreating the missing portions of images and each method's ability to recreate a realistic image.

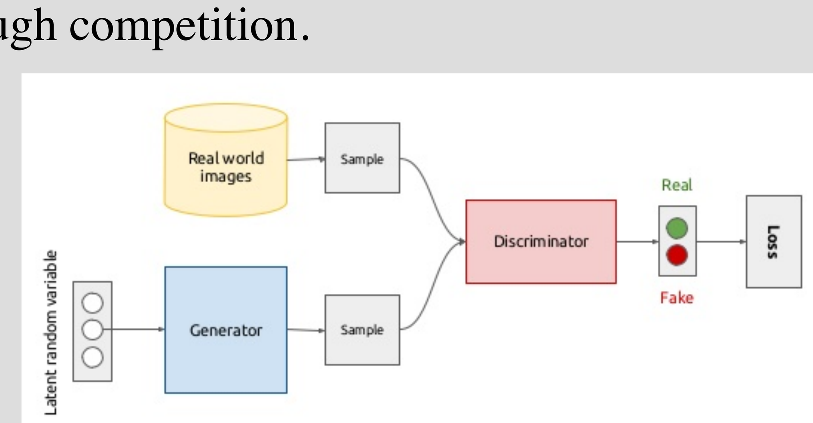
BACKGROUND AND SIGNIFICANCE

The task of filling in missing portions of images, known as inpainting, has been a subject of interest in the research community for a number of years. Inpainting has numerous real-world applications, such as restoring damaged images, or replacing unwanted areas of a picture. An interesting idea is a form of adblock: advertisements in photographs (such as signs, billboards, etc) can be removed and filled in naturally. Another way to look at our research is from an implication view: in order to realistically fill in an image gap, our network not only must be able to interpret how the real world looks like to obtain a context, but be able to recreate it. "In order to create something, one must first understand it."

With the rise of modern computer power, neural networks have become a go-to solution. The neural network can be seen as a pattern recognizer: if a computer is given many pairs of data, it can find correlation between the two. Specifically, we make use of the convolutional neural network, which contains a structure designed for use with images.



When training neural networks on images, the standard objective function is to minimize the mean squared error between generated and real images. Another method, however, is to learn the objective function as well. The generative adversarial network uses an additional neural network, the discriminator, which is trained to tell generated and real images apart. The discriminator and generator networks train simultaneously, and improve their outputs through competition.



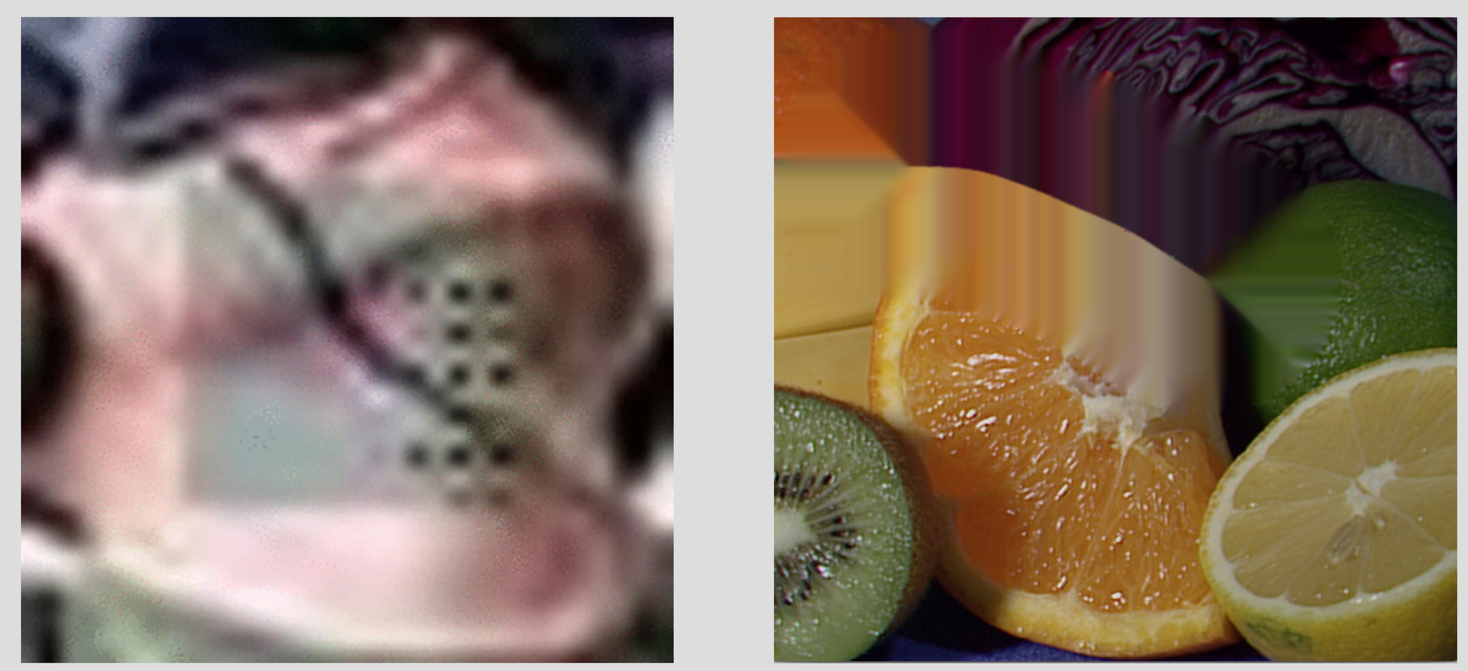
We also compare to purely mathematical models such as the Navier-Stokes model, which infers the missing portions of images using the Navier-stokes flow equations, and use it as a basis for comparing how well our research does.

RESEARCH METHODOLOGIES

We tested multiple models for comparison:

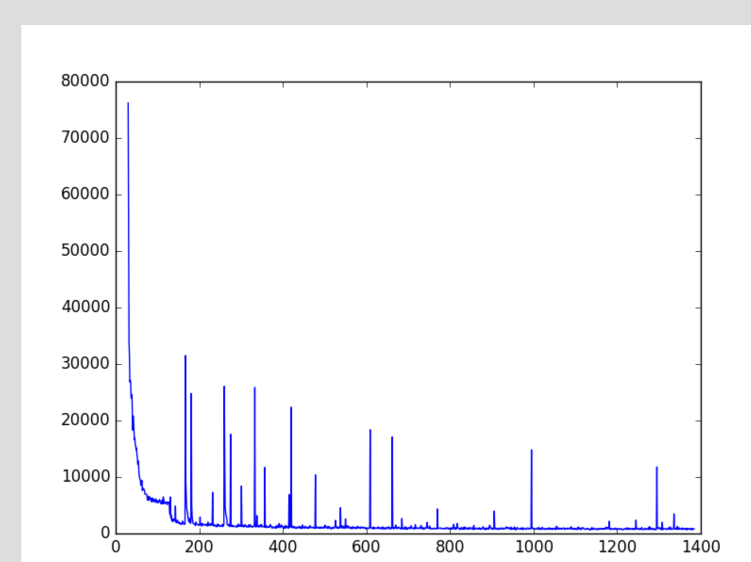
- Navier-Stokes model
- Convolutional Neural Network
- Generative Adversarial Network.

1. For testing purposes, we made use of the celebA dataset, which contains thousands of celebrity face images. We crop out the center portion of each image and task the networks with recreating it.
2. We implemented our models in python, utilizing the Tensorflow framework as well others such as OpenCV and scipy. The code was run on an NVIDIA 690 GPU, and took approximately 6 hours to converge.
3. We loop through the dataset until convergence -- when the error rate converges to a low percentage and no longer seems to improve.



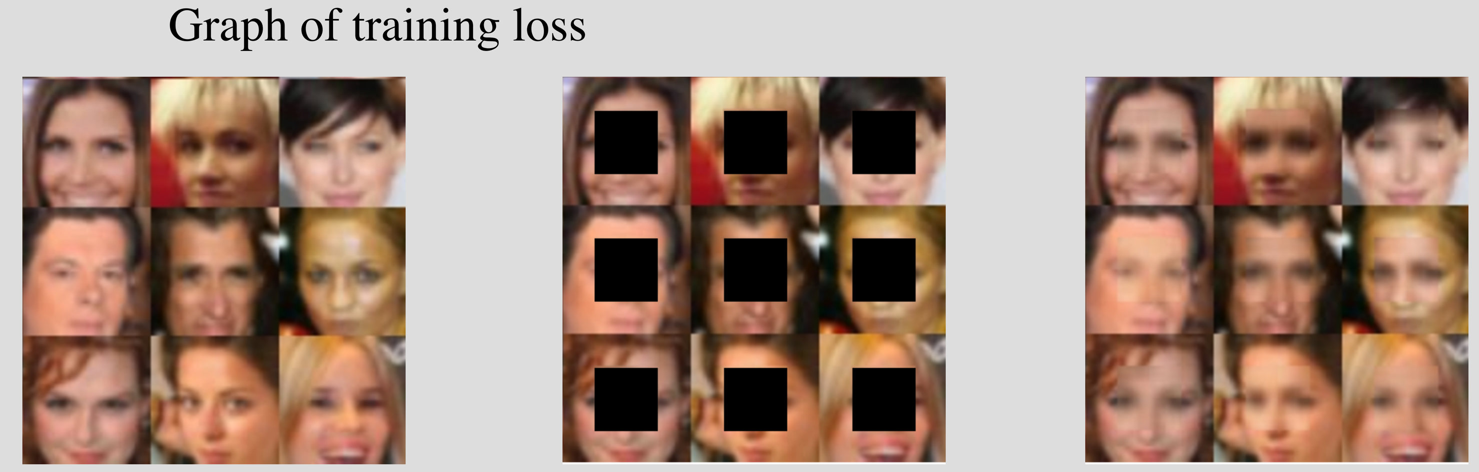
Examples of badly recreated images

RESULTS



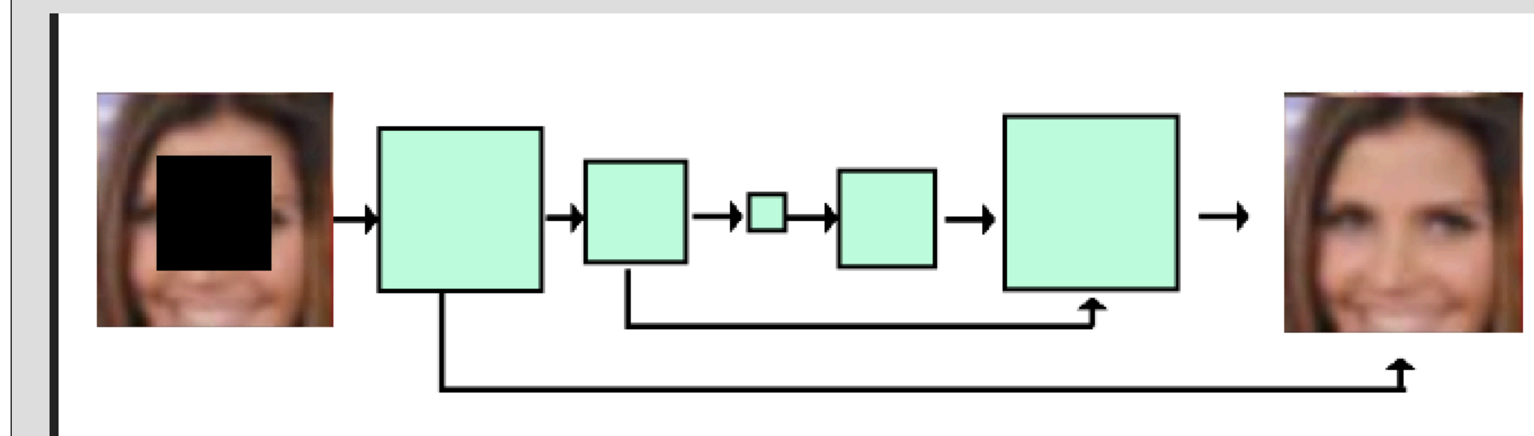
Graph of training loss

- Training loss converges to a low point
- Common features such as eyes and noses are clear
- Blurry areas appear where there is the most variability



From left to right: original image, given context, recreation.

MODEL STRUCTURE



The convolutional neural network starts with a large picture input, and shrinks height and width while increasing feature dimensions. At the halfway point, the reverse is done, until reaching original size.

CONCLUSION

- ➢ Using both simple convolutional networks, as well as generative adversarial networks, we can accurately reconstruct images ranging from faces to landscapes.
- ➢ Much better than purely mathematical methods such as the Navier Stokes Model.
- ➢ Future work could focus on reducing blurriness, scaling the network to bigger images, and recreating non-square portions.
- ➢ Could also implement feature networks, ones that can predict the object to aid reconstruction.

ACKNOWLEDGEMENTS / REFERENCES

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