THE UNIVERSITY OF TEXAS AT AUSTIN

Vision Transformer-Assisted Analysis of Neural Image Compression and Generation

Master's Thesis Report

Official Code Repositories:

https://github.com/kliment-slice/thesis-code

https://github.com/kliment-slice/thesis-latex

Supervisors:
Prof. Dr. Alan C. Bovik
Prof. Dr. Rachel A. Ward

Author:
Kliment Minchev

May 5, 2022

Contents

List of Figures

List of Tables

Executive Summary

This work investigates a novel application of a Vision Transformer (ViT) as a quality assessment reference metric for generated images after neural image compression. The Vision Transformer is a revolutionary implementation of the Transformer attention mechanism (typically used in language models) to object detection in digital images. The ViT architecture is designed to output a classification probability distribution against a set of training labels. Thus, it is a suitable candidate for a new method for quantitative assessment of generated image quality based on object-level deviations from the original pre-compression image. The metric is referred to as a ViT-Score. This approach complements other comparative measurement techniques based on per-pixel discrepancies (Mean Squared Error, MSE) or structural comparison (Structural Similarity Index, SSIM). This study proposes an original end-to-end deep learning framework for neural image compression, latent vector representation, reconstruction, and image quality analysis using state-of-the-art model architectures. Neural image compression and reconstruction is achieved using a Generative Adversarial Network (GAN). Results from this work demonstrate that a ViT-Score is capable of assessing the quality of a neurally compressed image. Moreover, this methodology provides valuable insights when measuring GAN output quality and can be used in addition to other relevant perceived quality metrics such as SSIM or Frechet Inception Distance (FID).

Chapter 1

Introduction to Vision Transformers (ViT)

This chapter presents the reader with an introduction to Vision Transformers (ViT).

It covers the motivation as to why ViT, or a future development inspired by it, will have a profound impact on the future of image compression, analysis, and generation. This chapter presents evidence that a Transformer, or perhaps an evolved deep learning model with a similar architecture (i.e. generalizable and highly overparameterized) can be superior in compressing and evaluating the latent feature space of a digital image compared to present-day technologies.

This section summarizes the brief history of Transformer usage in deep learning. These generalized architectures are dominating state-of-the-art language models, as they are extremely efficient in packing relevant information within a one dimensional vector.

This introduction then proceeds to describe the principles of operation of a ViT, followed by its mathematical formulation. Finally, it covers currently available implementations in the form of pre-trained models and conclude with an explanation on the computational and financial constraints of training such demanding architectures.

1.1 Motivation

Transformers are presently considered to hold a great promise for the future of Deep Learning as a step towards Artificial General Intelligence. Due to their architecture, they are more generalizable, less prone to overfitting, and able to learn highly complex representations. The Transformer architecture has already been proven to make obsolete Recurrent Neural Networks (RNNs) in natural language models. Furthermore, the Vision Transformer (ViT) has outperformed certain Convolutional Neural Networks (CNNs) in image classification tasks. [Dosovitskiy et al., 2021]

Figure 1.1 below shows an increase in the popularity of research related to Vision Transformers.

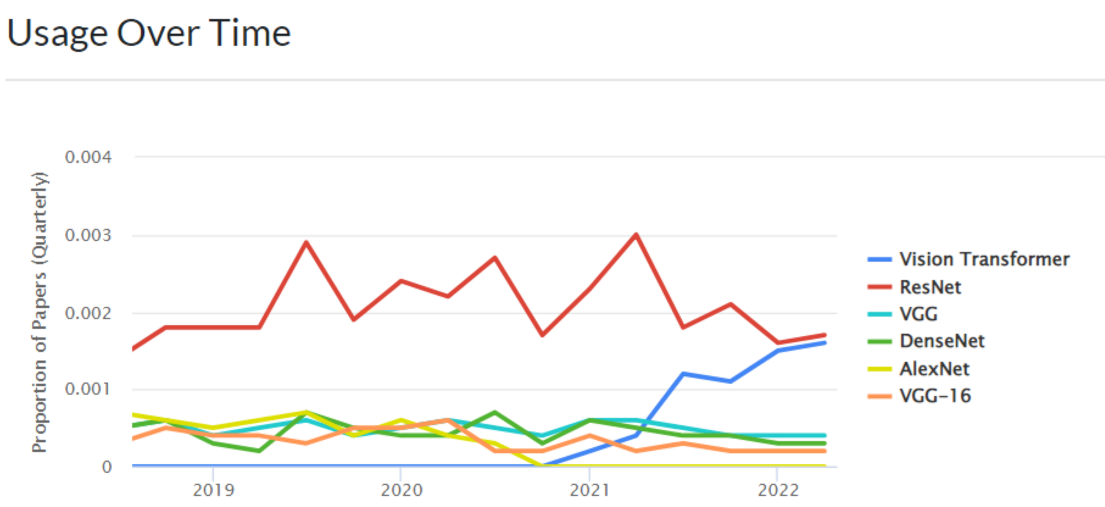


Figure 1.1: As of 2022, the usage of a Vision Transformer (ViT) in image tasks matches the usage of ResNets and has outnumbered any other popular CNN architecture. [PapersWithCode, 2022b]

Figure 1.1 was produced by PapersWithCode, a popular academic research aggregator. For the past three years, ResNets, the most popular architecture in image processing and computer vision, has dominated the proportion of academic research in object detection. In 2022, Vision Transformer research popularity has reached that of ResNets and exceeded any other major category.

In the zeitgeist of Vision Transformer research, this thesis explores a ViT-assisted metric related to image compression. This metric can provide additional insights to GAN output quality and the latent space (contextual) preservation of a variety of input images.

Thus, contributions from this thesis can be viewed as providing a stepping stone towards an end-to-end Transformer-based image compression and reconstruction framework.

1.2 Brief History

1.2.1 Attention and Language Models

"Attention Is All You Need" is a seminal research publication by a team of Google researchers, which kickstarted the Transformer revolution in Deep Learning in 2017. It proposes a novel architecture, which models long-range dependencies in sequential (text) data, by arranging a set of self-attention layers.

A self-attention layer is what the model uses to focus on different elements of the input sequence simultaneously. For example, it can be used to compute the distance (relationship) between every word in a given sentence. [Vaswani et al., 2017]

Examples of implementations of text-based Transformers are BERT by Google and GPT-3

by OpenAI. BERT, among many other applications, processes and autofills every single English-based Google user search query as of 2021 . [Nayak, 2022] GPT-3, on the other hand, revolutionized text generation in 2020, demonstrating the ability to generate extremely cohesive textual output.

Most Transformers are used for applications in language modeling and Natural Language

Processing (NLP). Thus, they are often benchmarked against Recurrent Neural Networks (RNNs, and specifically Long Short-Term Memory, LSTM architecture). LSTMs rely on hidden states to pass information along sequentially during the encoding and decoding process for each word token. However, they typically fall short learning long-range dependencies.

1.2.2 Attention in Vision Tasks

The attention mechanism is capable of focusing on objects found anywhere on an input image. It operates within a single network layer compared to Convolutional Neural Networks (CNNs), where the variable size convolution kernels scan across the different layers of the architecture. [Dosovitskiy et al., 2021]

As shown in Figure 1.2 below, tokenization happens at the pixel level, i.e. each pixel attends to each other pixel in the grid. This becomes computationally intensive, on the order of $(n^2)^2$, where n denotes width of a square image. To resolve this, the input image is broken down into square blocks of equal size, referred to as image patches. Then, each image patch is unrolled into a one-dimensional sequence $(nx1)$ and indexed with a positional embedding in a table for future reference and retrieval purposes. The embeddings enter the Transformer and finally, a feed forward classifier, in the form of a Multilayer Perceptron (MLP) makes the classification prediction, yielding a probability distribution. [Dosovitskiy et al., 2021]

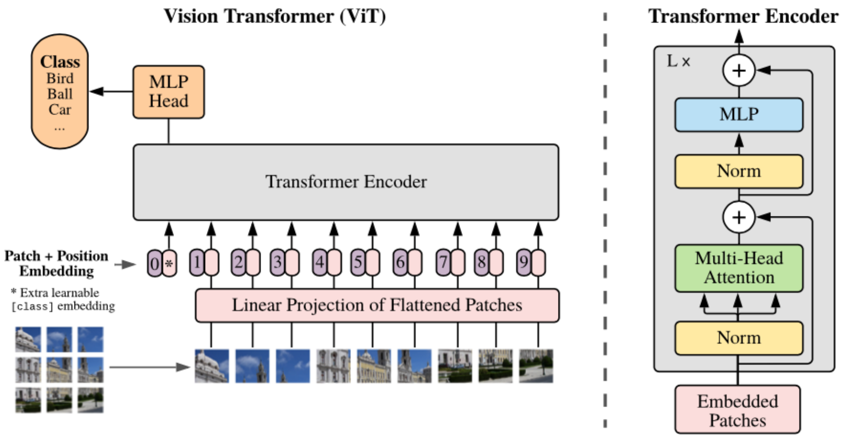


Figure 1.2: The Vision Transformer (ViT) architecture. [Google-Research, 2022]

A Transformer, in a way, is a generalization of a feed forward network, but instead of fixed connections weights in an MLP, each connection weight (i.e. attention) is computed ad hoc. This makes the Transformer, unlike the MLP, permutation invariant. That is, it would not know where certain information is coming from, unless there are additional learnable sequential positional embeddings, i.e. index the image patches.

1.3 Principles of Operation

Continuing from the previous section, a ViT can be thought of as a generalization of an MLP, which itself is a generalization of a CNN. The ViT happens to learn very similarly to a CNN, which represents the latent space as filters carrying principal components.

In principle, CNNs have good inductive priors and can learn any function. However, they promote locality, i.e. nearing pixels are probability-wise considered most important. This may easily not be desired, especially in the key applications of object detection and, in the future, image compression.

The encoding process indexes embeddings. For instance, certain key words in a sentence or objects in image blocks are mapped in a reference lookup table. The Decoder outputs Keys at each step. These vectors represent hidden states, which are being passed on into each next iteration of the Transformer. The last layer, expectedly, uses a Softmax architecture to normalize and map the potential output classes to a probability distribution.

Multi-Head Attention

As shown in Figure 1.3 below, sets of parallel attention layers at each token are called multi-head attention. This approach varies what to pay attention to, for example,at the different objects in an image (or in natural langue, different verbs in a sentence). The multi-head attention is composed of Key-Value pairs coming from the encoding part of the source image (i.e. the input embedding) and Queries from the output embedding (i.e. encoding part of target image).

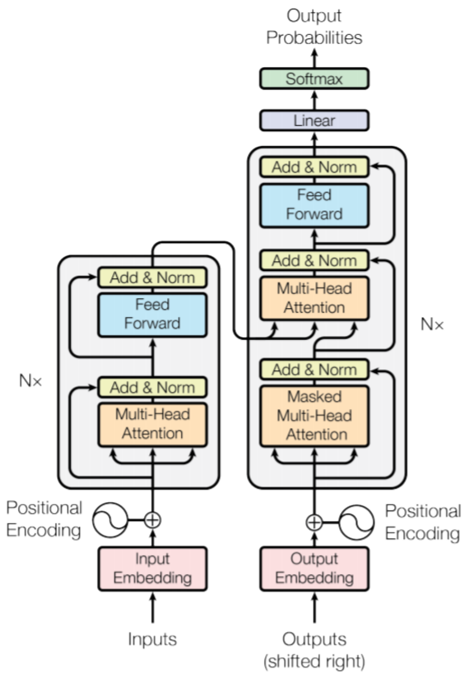


Figure 1.3: The Attention mechanism architecture. [Google-Research, 2022]

1.4 Mathematical Formulation

Attention

In its full formulation, Attention is a function of vectors representing Queries, Keys, and Values, labeled as (Q,K,V). Attention equals the dot product (QK^T) of Keys and Queries respectively, softmaxed over the square root of dimensions and multiplied by the Values vector.

To provide intuition:

Values are what is most interesting in the source image, i.e. attributes or structural features. In text, a Value could be important adjectives before each keyword, which provide emphasis in a given input sentence. Keys, on the other hand, index (or address) those Values (e.g. name, type, weight). Each Key has an associated Value. Queries are built by the encoder of the target image and prompt the network to find closest available information (Key and its corresponding Value).

$$Attention(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}}V)$$

Thus, the overall dynamic is that a Query is pegged against a Key to locate a certain Value.

Softmax

The Softmax function is defined as a normalized exponential function. A sequence of variables is mapped into exponentials and divided by the sum of all exponentials. Thus, the large numbers become almost ones and small numbers near zeros. Softmax is similar to the maximum function, with a key difference that Softmax is differentiable.

$$\sigma(Z_i) = \frac{e^{z_j}}{\sum_{j=1}^{K} e^{z_j}} \text{ for } i = 1,\ldots,K \; and z = (z_1,\ldots,z_K) \in \mathbb{R}^K$$

Thus, a Softmax of an inner product of each Key with Query vector normalizes to a probability distribution over all Values. Neural networks typically utilize a softmax in their last layer over all the classification labels. This yields the top classification by probability. Using the softmax function, a certain Key will stand out (in magnitude) vs the rest.

Vector Similarity

Vector proximity between embeddings represents the similarity between objects in images, or word connotations in sentences.

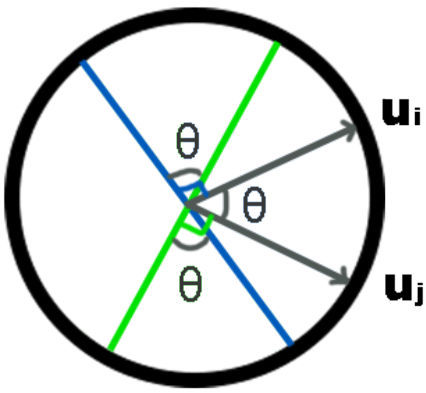


Figure 1.4: Vector representation on a unit circle.

The dot product of Keys and Queries yields an angle between both vectors (e.g. u_i and u_j in Figure 1.2 above) to measure how similarly aligned they are. In high dimensional spaces, most vectors would be orthonormal to each other and $cos(90) = 0$. But if Key and Query vectors are similar or align, they'd have a large dot product. The larger the similarity, the larger the dot product. The Query vector is computed with each Key in the surrounding vector space and softmaxed to select the one Key with the highest dot product. The selected Key in space has an associated Value. In applications, that Value would correspond to a match with a labeled object in an image, or perhaps the next word in a generated sentence.

A depiction of the vector space is shown in Figure 1.3 below.

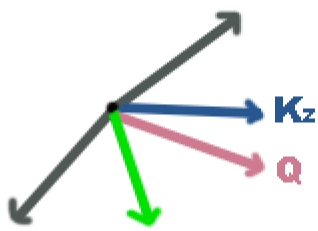


Figure 1.5: Vector proximity shows the closest Key vector to a given Query vector in space.

1.5 Implementations

This section reviews several notable ViT implementations of interest. Most developments have been made open source. However, some of the highest quality implementations are still closed source and operated under a license or payment wall.

1.5.1 Open Source

The academic research aggregator PapersWithCode lists 96 open source implementations of the original ViT from "An Image is Worth 16x16 Words" discussed in Chapter 2. The publication was made for ICLR 2021. [PapersWithCode, 2022a]

The original model from the team of Google researchers, written using TensorFlow, has 72,567 stars in its GitHub repository. The second highest implementation by Hugging Face, written using PyTorch, has 61,820 stars.

Pre-trained Model Used

For the purpose of this thesis, a PyTorch implementation was used trained on ImageNet-21k and fine tuned on ImageNet-1k. The ViT has 9,696 stars on its GitHub repository, ranking as the 5th highest rated implementation. It was chosen due to its reliability, project maturity, and interfaceability. [PapersWithCode, 2022a]

A python pip package is also available on PyPI from the same "lucidrains" implementation, which can be installed via:

```
"pip install pytorch_pretrained_vit"
```

Other pre-trained models are also availabe on GitHub and Google Colab. Some suffer from a lower GitHub star rating, are not well packaged (not object-oriented), or perhaps deviate too far from the original implementation of "An Image is Worth 16x16 Words".

1.5.2 Closed Source

Several modified implementations targeting specific generative applications have been made by Hugging Face and OpenAI. OpenAI has expanded from its success from GPT-3, a text generation Transformer, to visual applications.

Transformers and Vision Transformers can be used to find context in image objects from the latent space of an input image.

CLIP, Image GPT, DALL.E, and DALL.E2 by OpenAI bridge the gap between textual information and images. DALL.E 2, the highest quality image Transformer to date, was released in April 2022. It is trained on 250M image-text pairs to be able to generate coherent images from textual description. [OpenAI, 2022]

Most of OpenAI's Transformer developments (e.g. GPT-3, DALL.E 2) have not been open sourced. Google's ViT and BERT, however, have been.

1.6 Computational Constraints for Training

The main reason for using a pre-trained ViT is that the Transformer architecture is so generalizable and overparameterized, that the computational requirements for Time, Memory, and Cost of training are beyond the scope of this thesis.

For example, GPT-3 was trained on 45TB of text data (all of Wikipedia included). It has 175B parameters and 96 attention layers. [Li, 2022] One flavor of GPT-3 (of many) alone cost $4.6M to train using the most advanced Nvidia datacenter GPUs in a cluster.

The original ViT implementation from "An Image is Worth 16x16 Words" took 2.5k core-days of training time. [Dosovitskiy et al., 2021]

Training the Next Generation of Image GPT

It would require several orders of magnitude more resources to train a Vision Transformer that matches the quality of GPT-3 for generative text applications.

The training data would need to be similar to all Google images on the internet (or at least a respectable representative subset). It would probably cost on the order of $50M in training alone, since image matrices are two-dimensional sequences of data. Contextual complexity also rises exponentially for images compared to text.

Chapter 2

Background Review: Transformers and Neural Image Compression

This chapter serves to present the audience with a literature review of seminal academic publications and relevant background information relating Transformers to image compression and generation.

Necessary formulations of Generative Adversarial Networks (GANs), Image Compression, and Image Quality Assessment (IQA) are also provided to aid the reader's understanding of this thesis project.

Among much of the domain knowledge available, the reader would find interest in the takeaways offered from:

- "An Image is Worth 16x16 Words" [Dosovitskiy et al., 2021]
- "Towards End-to-End Image Compression and Analysis with Transformers" [Bai et al., 2022]
- Overview of Image Generation with GANs
- "First Principles of Deep Learning and Compression" [Ehrlich, 2022]
- Image Quality Assessment (IQA) metrics [Documentation, 2022]

2.1 "An Image is Worth 16x16 Words"

Transformers for Image Recognition at Scale

This seminal academic work was published in the International Conference on Learning Representations (ICLR) 2020 by a team from Google. It presents the first Vision Transformer (ViT) for object detection trained on the ImageNet dataset, a rather large natural images dataset common to research on image classification.

Since Chapter 1 already explained and formulated the ViT in detail, this section focuses on outlining the outcomes from this publication. Refer to Figures 1.2 and 1.3 from Chapter 1, which were originally developed for this paper.

The Self-Attention mechanism, detailed in section 1.2.2, is key to defining where the Transformer is able to find a certain object on an image. Notice the self-attention map plotted on top of the original images in Figure 2.1 below:

Figure 2.1: The attention map is plotted and superimposed on the original images from the paper. [Dosovitskiy et al., 2021]

"An Image is Worth 16x16 Words" completely discards the notion of convolutions. The team used an image patch-based approach by breaking the image down to square blocks called patches. These patches are used as embeddings to a Transformer to classify images.

Comparison between the position embeddings using cosine similarity points the transformer into forming the object detection attention map. Figure 2.2 below shows a representation.

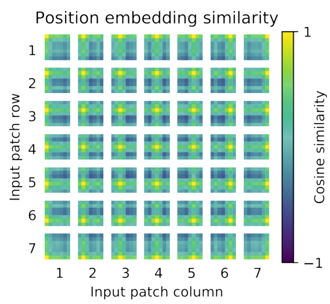


Figure 2.2: The image patches are compared to each other using cosine similarity to yield an indexed embedding map guiding the self-attention mechanism. [Dosovitskiy et al., 2021]

Typically, such object detection tasks in this field of research are dominated by Convolutional Neural Networks (CNNs).

However, the ViT model achieves a top-1 accuracy (matching highest class probability only) of 77.3% on ImageNet, which compares to the accuracy of state-of-the-art CNNs.

According to the paper, the pre-trained ViT on the JFT-300M dataset beats all ResNets on all datasets. Furthermore, it takes significantly less computational resources to train. [Dosovitskiy et al., 2021]

Compared to its convolutional counterpart (the ResNet), the ViT cost 75% less resources to train and outperformed on ImageNet accuracy by 1%. ViT uses approximately 2-4x less compute to attain the same performance (averaged over 5 test datasets).

The total number of parameters is on the order of 100M.

Some of the results from the original publication are shown in Figure 2.3 below.

Model	Layers	Hidden size D	MLP size	Heads	Params
ViT-Base	12	768	3072	12	86M
ViT-Large	24	1024	4096	16	307M
ViT-Huge	32	1280	5120	16	632M

Table 1: Details of Vision Transformer model variants.

	Ours-JFT (ViT-H/14)	Ours-JFT (ViT-L/16)	Ours-I21K (ViT-L/16)	BiT-L (ResNet152x4)	Noisy Student (EfficientNet-L2)
ImageNet	**88.55** $\pm$ 0.04	87.76 $\pm$ 0.03	85.30 $\pm$ 0.02	87.54 $\pm$ 0.02	88.4/88.5*
ImageNet ReaL	**90.72** $\pm$ 0.05	90.54 $\pm$ 0.03	88.62 $\pm$ 0.05	90.54	90.55
CIFAR-10	**99.50** $\pm$ 0.06	99.42 $\pm$ 0.03	99.15 $\pm$ 0.03	99.37 $\pm$ 0.06	–
CIFAR-100	**94.55** $\pm$ 0.04	93.90 $\pm$ 0.05	93.25 $\pm$ 0.05	93.51 $\pm$ 0.08	–
Oxford-IIIT Pets	**97.56** $\pm$ 0.03	97.32 $\pm$ 0.11	94.67 $\pm$ 0.15	96.62 $\pm$ 0.23	–
Oxford Flowers-102	99.68 $\pm$ 0.02	**99.74** $\pm$ 0.00	99.61 $\pm$ 0.02	99.63 $\pm$ 0.03	–
VTAB (19 tasks)	**77.63** $\pm$ 0.23	76.28 $\pm$ 0.46	72.72 $\pm$ 0.21	76.29 $\pm$ 1.70	–
TPUv3-core-days	2.5k	0.68k	0.23k	9.9k	12.3k

Figure 2.3: Results summary from the original ViT by Google. It shows the ViT performance on popular classification benchmarks. [Dosovitskiy et al., 2021]

2.2 "End-to-End Image Compression with Transformers"

A recent publication in Association for the Advancement of Artificial Intelligence (AAAI) 2022 is claiming to have achieved an end-to-end Transformer-based model for image compression and analysis.

"Towards End-to-End Image Compression and Analysis with Transformers" redesigns the ViT to classify images from compressed features. [Bai et al., 2022]

The research team replaces the patches and embeddings with a CNN-based lightweight encoder. The compressed latent space features from the encoder are fed into the Transformer. The Transformer proceeds to classify the image without any regeneration or reconstruction. The framework includes a feature aggregation module, which blends the compressed and intermediate Transformer features. These features are then passed onto a Deconvolutional Neural Network and the image is regenerated. As a result, long-term dependencies from the Transformer self-attention mechanism are preserved.

Figure 2.4 below demonstrates the exact architecture used in the experiment.

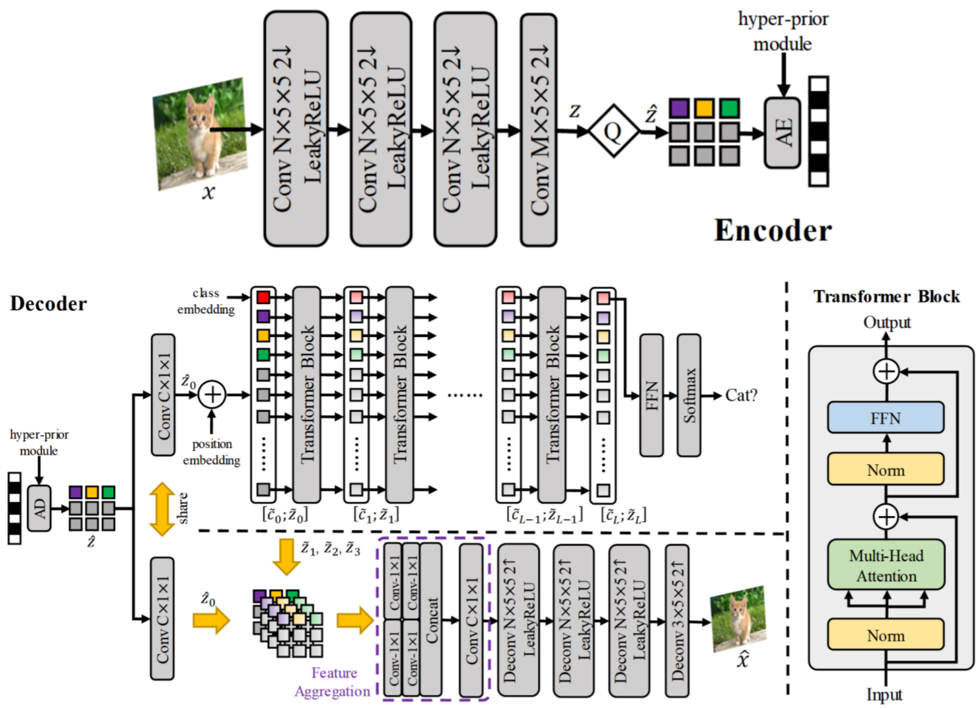


Figure 2.4: The encoder and decoder architecture of the End-to-End Image Compression ViT. [Bai et al., 2022]

2.3 Overview of Image Generation with GANs

Generative Adversarial Networks (GANs) have long been considered to be the most exciting innovation in Deep Learning. In a typical GAN architecture, two CNNs are competing against each other. One network is called the Generator, whose purpose is to generate an image. The other network is called the Discriminator, whose purpose is to determine how realistic the generated output by the Generator is.

The Discriminator communicates feedback to the Generator after each epoch through a loss function. The Discriminator is trained to minimize the loss, while the Generator is maximizing it. The Generator iteratively learns to create new synthetic images resembling real source input image. Then, the Discriminator is trained to differentiate between the real input data and generated synthetic data. The desired outcome is that a Generator would be able to fool the Discriminator that its synthetic output is real. [Pathmind, 2022]

In essence, the Discriminator provides feedback to the Generator on its performance, while simultaneously achieving incremental improvements in its own discernibility.

As a result, after each epoch, the Generator is expected to produce increasingly more realistic data, according to a quantitative or qualitative (visual inspection) metric. In turn, the Discriminator becomes better at catching synthetic output, thereby having both networks compete against each other to refine the final generated image output.

Figure 2.4 below illustrates the architecture of a common GAN. Starting from random noise, the Generator is iteratively trained to produce a quality generated image. That image is then evaluated by the Discriminator whether it is real or synthetic.

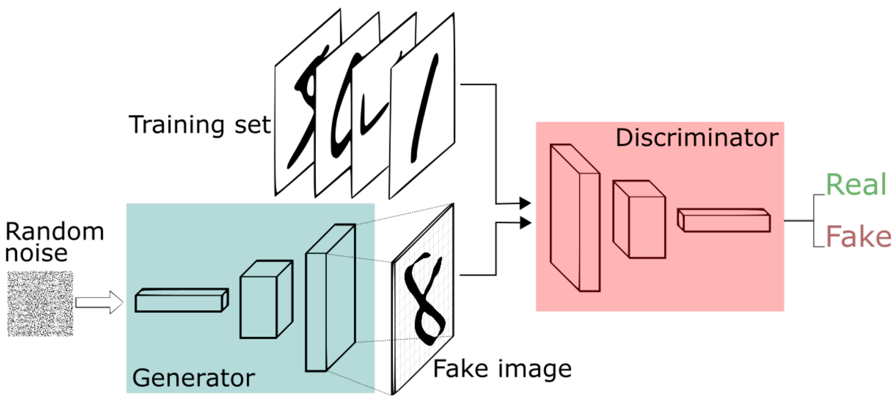


Figure 2.5: The architecture of a simple Generative Adversarial Network. [Pathmind, 2022]

Several common GAN applications include generating missing data (versus deterministic interpolation), synthetic data, image-to-image translation, medical imaging, and art.

2.4 First Principles of Neural Image Compression

The explosion in popularity of Deep Learning methods as universal function approximators is expected to revolutionize image compression. The key reason is that neural networks could achieve orders of magnitude higher compression than lossy deterministic methodologies. They can extract relevant information from the latent space of the image and are extremely efficient at packing it into a condensed version. The resulting compressed representations would require much less disk space or bandwidth for transmission.

Presently, efficient storage and transmission of image and video is still a developing and costly domain. Thus, a Deep Learning approach to multimedia compression would, theoretically, enable higher compression ratios and an increase in visual quality. This approach would train a model to learn a compression function directly from data. Referred to as "Learned Multimedia Compression", this approach involves computing a compressed representation of an input image. It uses separate models for both the encoder and decoder. [Ehrlich, 2022]

Finally, a Deep Learning-based method could learn key steps of established deterministic compression algorithms. This approach would serve as an improvement to the existing framework of popular compression techniques. The most popular image compression technique is the Joint Photographic Expert Group format, JPEG, created in 1992. In short, it operates by using a Discrete Cosine Transform (DCT) to convert image information from the spatial to frequency domain. Then, the compression algorithm discards high-frequency information, as it is not relevant to human visual perception. [Ehrlich, 2022]

Figure 2.6 illustrates JPEG compression at various thresholds, along with the compression ratios of each compressed image.

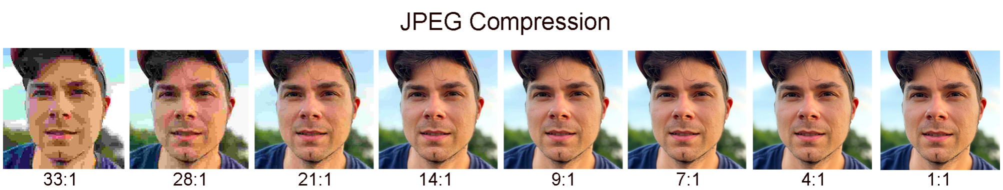


Figure 2.6: A neural compression model would have to outperform JPEG in compression ratio vs reconstructed image quality. [Pathmind, 2022]

An example of a Deep Learning-based compression model could be to improve the compression fidelity (output quality, compression ratio, and speed) of JPEG. To prevent information loss, a model can be trained to predict non-linearities in the compressed image related to blurring or noise. Furthermore, a model could learn image correction maps to correct distortions caused by JPEG compression. It can be trained to learn the latent feature space from example pairs of corrected JPEG compressed images and their ground-truth originals.

2.5 Metrics for Image Quality

Image Quality Assessment (IQA) is a methodology to evaluate distortions, aberrations, or degradations in perceived image quality.

To evaluate the quality of a reconstructed image and benchmark the ViT-Score, this thesis will use the following metrics:

- Structural Similarity Index (SSIM)
- Mean Squared Error (MSE)
- Peak Signal-to-Noise Ratio (PSNR)
- Frechet Inception Distance (FID)
- Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE)

SSIM

SSIM is a measure of the similarity between two images, on an interval $[-1,1]$.

The higher SSIM value indicates a more similar image to the reference.

It is based on the computing and combining three components: Luminance, Contrast, and Structure. Luminance measures image brightness. Contrast measures how dark and bright pixels are distributed in an image. Structure captures edge definition. [Wang et al., 2004]

The exact mathematical formulation is:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + (k_1L)^2) + (2\sigma_{xy} + (k_2L)^2)}{(\mu_x^2 + \mu_y^2 + (k_1L)^2)(\sigma_x^2 + \sigma_y^2 + (k_2L)^2)}$$

Where, given a windows x and y of size (N,N):

μ_x is the average of x' μ_y is the average of y; σ_x^2 the variance of x, σ_y^2 the variance of y; σ_{xy} the covariance of x and y; L is the pixel value dynamic range, i.e. $2^{\#bitsperpixel} - 1$; and by default, given as constants are $k_1 = 0.01$ and $k_2 = 0.03$ [Wang et al., 2004]

MSE

MSE is a measure of the average squared error between an input and reference matrix (i.e. image).

The lower the MSE value, the better the image quality.

The mathematical formulation is:

$$MSE = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (x_{ij} - y_{ij})^2$$

Where: m, n is the rows and columns of the input image, x_{ij} and y_{ij} are pixel values from the input and generated image respectively. [Documentation, 2022]

PSNR

PSNR is the ratio between the maximum possible signal intensity value and the corrupting noise present in the same signal. The higher the PSNR value, the better the image quality. [Documentation, 2022]

The mathematical formulation becomes:

$$PSNR(x,y) = \frac{10 \log_{10} [\max(\max(x), \max(y))]^2}{|x - y^2|}$$

FID

Commonly used in analyzing GAN output quality, the Frechet Inception Distance (FID) compares two multidimensional Gaussian distributions.

Given are:

$\mathcal{N}(\mu, \Sigma)$, representing neural network features of the GAN generated image.

and

$\mathcal{N}(\mu_w, \Sigma_w)$, representing the same features from the real images in a training dataset. [Brownlee, 2022]

Thus, the mathematical formulation is:

$$FID = ||\mu - \mu_w||_2^2 + tr(\Sigma + \Sigma_w - 2(\Sigma^{1/2}\Sigma_w\Sigma^{1/2})^{1/2})$$

BRISQUE

BRISQUE represents a referenceless image quality methodology where 0 is the perfect score and 100 worst. This score could be interpreted as tendency of an image to be photorealistic. The score is derived from the Gaussian properties of natural scene statistics found in images. Image quality is evaluated for the presence of corruption caused by blurs or graininess. An image with no distortions often has a score below 5. [Mittal et al., 2012]

BRISQUE may be too simple to evaluate user-generated content, but is nonetheless useful in comparing it to the ViT-Score.

Chapter 3

ViT-based Assessment of Neural Image Compression

This chapter presents the core contributions from this thesis. Four input images are used to demonstrate the modest ability of a GAN to compress and reconstruct from latent space. The section explains the architecture of choice and presents the output from the GAN. The audience is presented with visualizations of the training process, latent space vector, and resulting Compression Ratio (CR) values. The reader is free to visually inspect the output. The novel ViT-Score and its mathematical formulation is presented. The output post-compression images are also evaluated using the following image quality metrics: SSIM, MSE, PSNR, FID, BRISQUE.

Finally, a summary table presents all results from this chapter for quick reference.

3.1 Architecture and Inputs

3.1.1 General Project Architecture

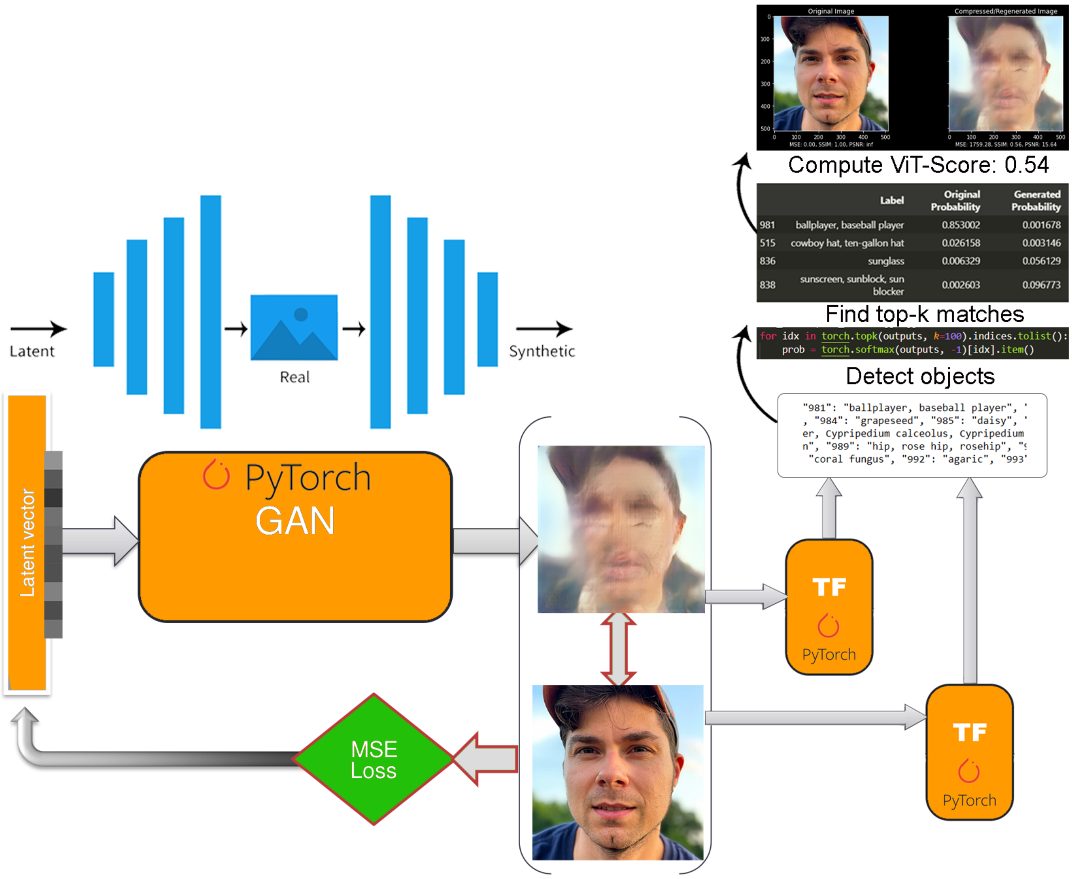


Figure 3.1: The engine architecture for this project. A GAN compresses and reconstructs an input image. Then, a Vision Transfomer (ViT) conducts object detection in both the input and generated images. Finally, the ViT-Score is computed based on the number of matching labels.

A standard Generator-Discriminator architecture GAN was used.

The Generator generates a synthetic image for the Discriminator to evaluate. Stochastic Gradient Descent (SGD) optimizer was used for the GAN to find the most optimal latent space vector representation of the input image. Mean Squared Error (MSE) was used as a Loss function.

A pre-trained Vision Transformer (ViT) was used for the image labeling.

3.1.2 Image Compression Diagram

Similar to established image compression methodologies, the compression and reconstruction process is divided into a Compressor and Decompressor parts.

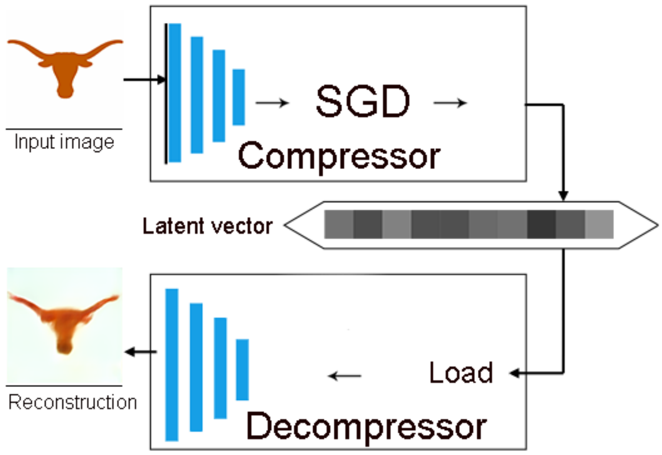


Figure 3.2: The Compressor-Decompressor uses the GAN Generator from Figure 3.1 above to generate the output image using most optimal latent vector representation.

As showing in Figure 3.2 above, the Compressor is composed of the GAN Generator and an input image to find and return the latent vector using Stochastic Gradient Descent (SGD).

The Decompressor then uses the GAN Generator and latent vector from the Compressor to produce the final reconstructed image.

Following the Decompressor generating an output image, the pre-trained ViT then detects objects from a dictionary of labels. The ViT outputs a probability distribution, i.e. a probability for each label summing to unity (softmax). The final output of the script developed for this project is the ViT-Score, and other relevant image quality metrics (e.g. SSIM, MSE, etc) to evaluate the generated output image.

Python and PyTorch were used for the implementation of the architectures detailed above.

3.1.3 Sample Input Images Used

Four images (512x512, PNG format) are used in this study. The images represent distinct types of image to be compressed, as well as diverse features to challenge the deep learning model architecture. For example, a white background ("Logo"), a black background ("Bevo"), similar shapes, but distinct images ("Logo" vs "Bevo"), a face, a building, trees and clouds in the background.

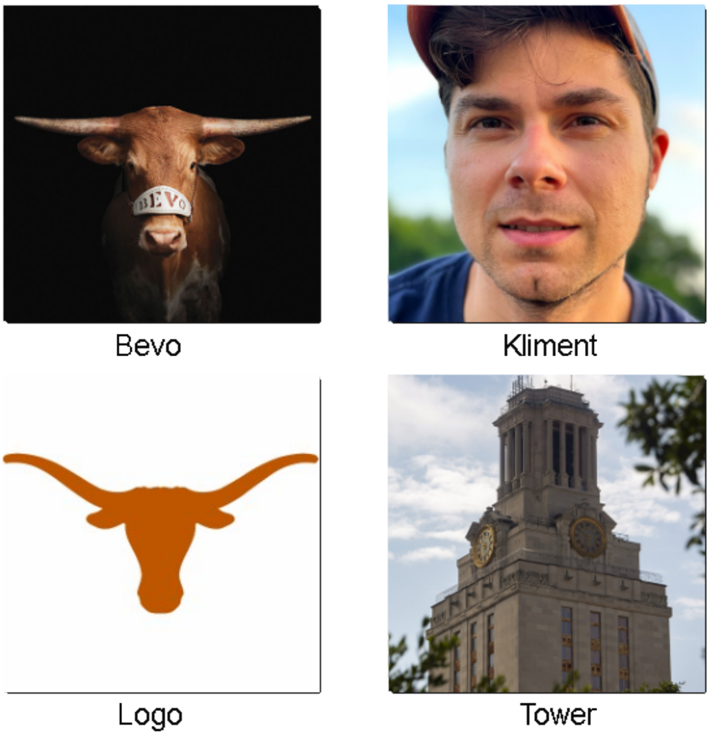


Figure 3.3: Input Images used in this project (512x512):
"Bevo": The University of Texas mascot, a famous longhorn bull.
"Kliment": A face portrait of the author.
"Logo": The Texas Longhorns logo.
"Tower": The University of Texas Tower, the Main Building on campus.

3.1.4 Latent space vector representation during compression

$nx1$ vector, where n corresponds to the height or width (in pixels) of a square input image. In the case of all input images used, the latent vector is of size $512x1$, since the input images are of size $512x512$.

hard to decipher but here is a zoomed in visual of the first This is what the GAN architecture compresses the full image to (1.54kb vs original size 409kb). The GAN then rebuils to 242kb.

Figure 3.4: Visual representation of the first 10 pixels in the most compressed version of the original image.

3.2 Outputs and Visual Inspection

The generative process from the GAN was designed to output an image at a specified epoch.

3.2.1 Training Process

Below is a demonstration of the GAN learning process at every 250 epochs:

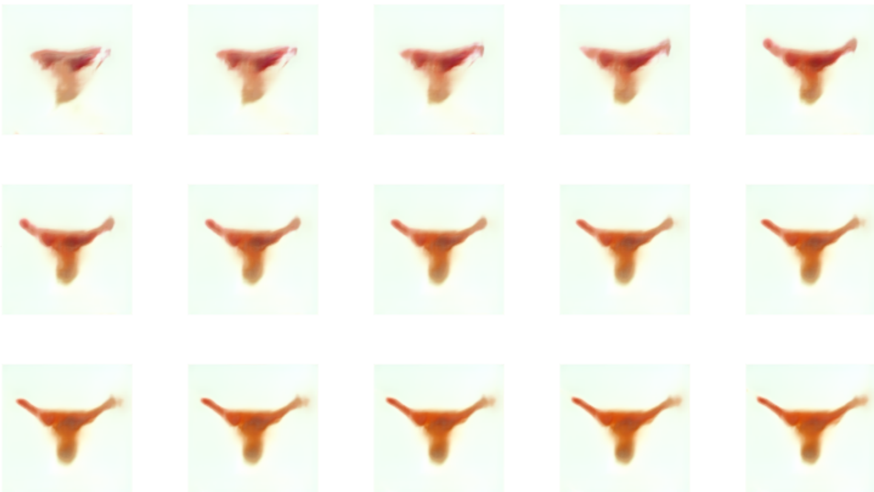


Figure 3.5: The GAN learns to compress and generate the Texas Longhorns logo.

Due to the cutting edge nature of the technologies used, a natural performance asymptote was observed. The GAN was able to reconstruct certain input images better than others. After a certain iteration, as usual, the GAN was unable to further learn how to compress, represent, and regenerate some input images. Typically, once a GAN reaches this stage, it learns from random noise and generation performance decreases.

3.2.2 Generated Results

Figure 3.4 below shows the resulting images from the neural compression GAN.

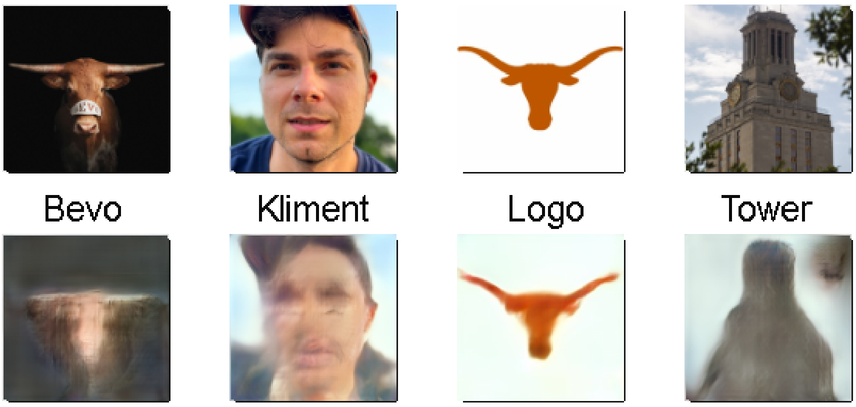


Figure 3.6: After sufficient training, the GAN outputs a regenerated version of the original image from a latent space vector representation.

The GAN was able to respectably regenerate "Kliment" and "Logo", especially if the resolution were to be lowered (e.g. 32x32, such as the CIFAR-10 dataset).

However, the GAN was unable to perform as well for "Bevo" and "Tower". It learned random noise and generation performance decreased.

Compression Ratios (CR)

Bevo	1.32 *(failed to compress)*
Kliment	0.59
Logo	8.28 *(failed to compress)*
Tower	0.54

Table 3.1: Compression ratios of generated images.

The GAN failed to compress two of the images, "Bevo" and "Logo". Understandably, "Logo" is actually a vector graphic with a clear background, with an input file size of only 13.4 KB. The GAN had to create the white background, which cost extra disk space.

"Kliment" and "Tower" were compressed to half the original size, with "Kliment" being a suitable candidate to demonstrate the capacity of this GAN. Much like the content of "Kliment", the most popular application and training set of most GANs, including this pre-trained model, is indeed faces. Hence, "Kliment" had the highest Compression Ratio (CR), while maintaining the highest ViT-Score.

3.3 ViT-Scores

The Vision Transformer-Assisted ViT Score is an original development from this thesis.

It is an attempt to measure the quality of a generated image after neural compression.

The ViT-score is in the open interval $(0,1)$ with 0 being poor and extremely dissimilar from the original and 1 being excellent and fully similar to original.

Mathematically, the endpoint values of the interval are unattainable by probabilistic models such as the GAN.

3.3.1 Mathematical Formulation

The following is a mathematical representation explained in further detail.

$$ViT_{score} = \frac{argmax_{A' \subset A, |A'|=k} \sum_{a \in A'} a}{k}$$

where $\sum_{a \in A'} a = \{m \in I_{input}\} \cap \{n \in I_{generated}\}$

and m are the top-K labels in the input image I_{input}

and n are the top-K labels in the generated image $I_{generated}$.

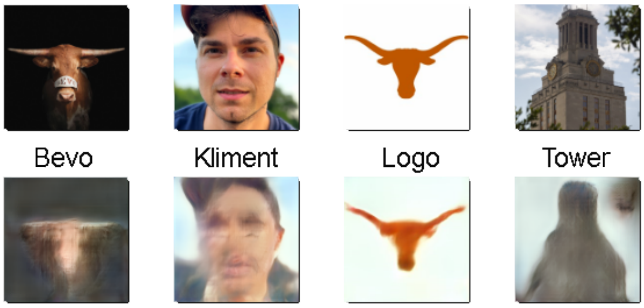
This overly elaborate mathematical notation is an attempt at describing:

"From the full set of trained ViT labels, we find the top-K number of intersecting labels between the original and generated images. Then, we divide that by K"

For example, of the top-100 labels found in the original image, identify the set of labels also found in the generated image. Then, divide that number of intersecting labels by the total number of 100 labels.

3.3.2 ViT-Scores from Resulting Images

Following Figure 3.7, the ViT-scores for the GAN generated images after neural compression are as follows:



Resulting generated images.

ViT-Scores

Bevo	0.14
Kliment	0.54
Logo	0.29
Tower	0.03

Table 3.2: ViT-Scores demonstrate a somewhat expected quality assessment.

"Kliment" leads with a ViT-score of 0.54, which is understandable as the GAN generated a face (although smudgy) and was rather able to recreate the scenery structurally.

"Logo" generation seems structurally excellent and the ViT-score is 0.29, which is considered a good score for this particular GAN architecture and training.

"Bevo" barely preserves the original shape at ViT-score of 0.14, while **"Tower"** is incomprehensible and barely resembles the original at ViT-score of 0.03.

Overall, the ViT-score does a good job of measuring image quality.

3.4 Established IQA Metrics

3.4.1 "Kliment"

Figure 3.7: The image was structurally reconstructed rather well. Shortcomings were only the facial features within the face.

This image achieved a ViT-Score of 0.54, SSIM of 0.56, and MSE of 1,759.28 with a Compression Ratio of 0.59.

3.4.2 "Logo"

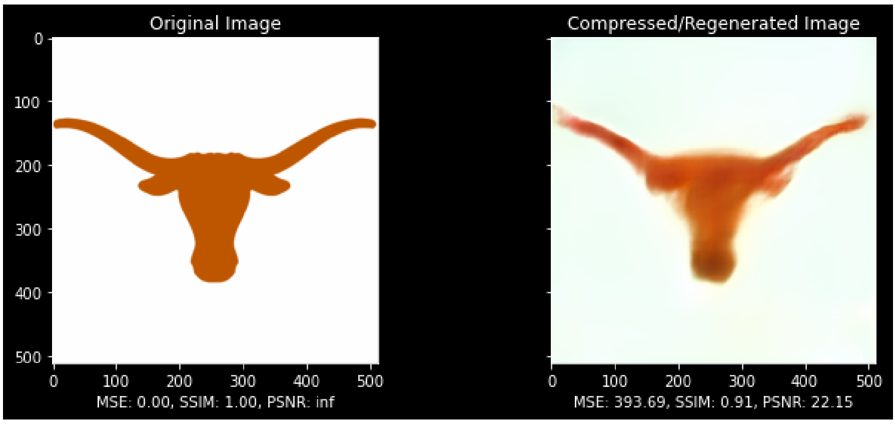


Figure 3.8: The GAN was able to reconstruct the logo almost perfectly.

The generated logo is extremely well identifiable. This image achieved a ViT-Score of 0.29, SSIM of 0.91, and MSE of 393.69. However, it failed to be compressed less than its original size. The GAN had to reconstruct the white background, which came out yellowish.

3.4.3 "Bevo"

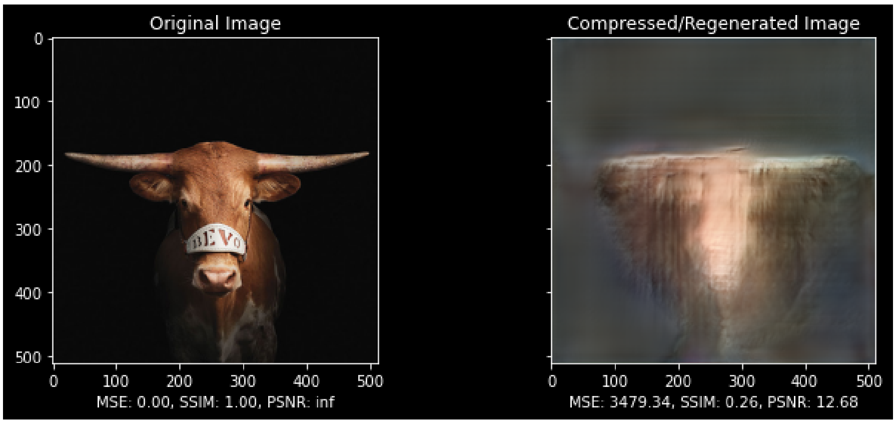


Figure 3.9: The GAN was unable to reconstruct inside the longhorn, yet the structure of the image is well rebuilt. One could possibly identify the animal from the generated image.

"Bevo" achieved a ViT-Score of 0.14, SSIM of 0.26, and MSE of 3,479.34, while failing to compress.

3.4.4 "Tower"

Figure 3.10: The GAN completely failed at .

This reconstruction is the lowest quality of all four images, both quantitatively and qualitatively. The generated image is incomprehensible. It has the lowest ViT-Score at 0.03, SSIM of 0.53, and MSE of 1,315.75.

3.4.5 "BRISQUE"

Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) where approaching 0 is a good score and approaching 100 is a bad score, the BRISQUE referenceless image quality methodology

This score could be interpreted as the image being more photorealistic than not. In terms of quality, this compares to a camera captured image with quality corruption caused by blurs or graininess. An image with no distortions often has a score below 5.

	Original	Generated
Bevo	32.9214	39.5535
Kliment	-8.3593	44.3570
Logo	102.9010	97.1844
Tower	14.5973	52.8363

Table 3.3: BRISQUE Scores of original and generated images.

Expectedly, the BRISQUE values for the generated images are always higher than their original counterparts. "Logo" is not a photorealistic image to begin with, so it is understandable that the BRISQUE value is high at 102.9. None of the generated images would pass BRISQUE as photorealistic and free of distortions.

Loss functions as well (MSE loss was used in GAN)

3.4.6 GAN-Related Quantitative Metrics

There are two prominent evaluation metrics for the performance of a Generative Adversarial Network (GAN). Specifically, the Frechet Inception Distance (FID) and Inception Score (IS).

The FID score is 0 if there is no difference between the two multidimensional Gaussian distributions compared.

Both measurements serve to evaluate the synthetic nature of the generated output.

The **FID** score is presented in Table 3.1 below:

Bevo	1,241,999.901
Kliment	549,089.491
Logo	81,105.162
Tower	331,171.556

Table 3.4: The Frechet Inception Distance (FID) score for all test images.

The FID score can be used as a Loss functions as well, embedded within the architecture of the GAN. However, it provides notoriously incosistent results, and is not as robut as MSE, which was used as the Loss function of choice for this project.

3.5 Summary of Results

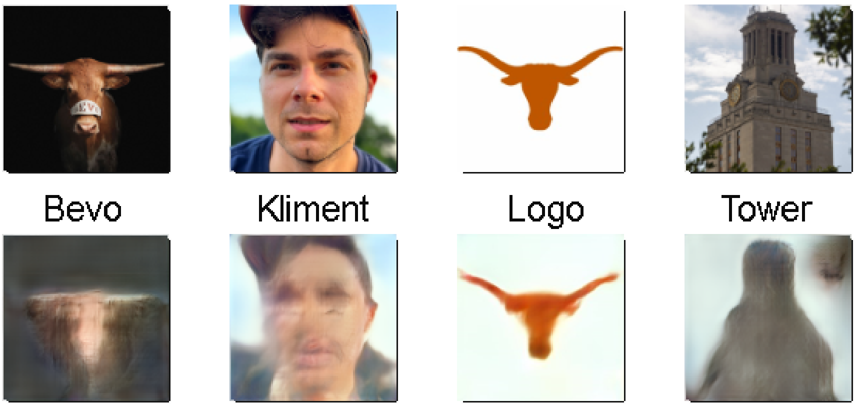


Image	ViT-Score	SSIM	MSE	PSNR	FID	BRISQUE	CR
Bevo	0.14	0.26	3,479.34	12.68	1,241,999.901	39.5535	1.32
Kliment	0.54	0.56	1,759.28	15.64	549,089.491	44.3570	0.59
Logo	0.29	0.91	393.69	22.15	81,105.162	97.1844	8.28
Tower	0.03	0.53	1,315.75	16.90	331,171.556	52.8363	0.54

Table 3.5: ViT-Scores provide an insightful quality assessment compared to established methods.

Chapter 4

Discussion

This chapter critically discusses the results from Chapter 3 in greater detail. The reader is presented with a thorough evaluation of the results, potential improvements, challenges, and possible optimization to the architecture. Based on the results shown, the reader is invited to a thought-provoking discussion of the present and future of image-based Transformers. Finally, the audience is engaged in a speculation on the cost of training a successful image compressing Transformer.

4.1 Results and Improvements

4.1.1 Results

The most incomprehesible generated image "Tower", where the GAN failed to reconstruct a recognizable object, expectedly has the lowest ViT-Score of all four images. This is a testament for the valuable insight the ViT-Score contributes.

PSNR, FID, and BRISQUE seem rather irrelevant due to their inability to capture synthetically induced aberrations obvious to the human eye.

4.1.2 Potential Improvements to Architecture

The ViT-Score definition could be further improved or experimented with. For the purpose of this project, the ViT-Score was based on how many of the top100 labels match between the input and generated images.

The ViT-Score can take into account probability of each label found (included in script output). While the label probability is stable when working with corrupted images, it is rather unstable when working with generated images.

Features are typically found to be in the deeper layers of the GAN network. The latent space is hard to decipher, but a Transformer is efficient in packing information from it to a 1-dimensional vector.

Evaluating output quality from Generative Adversarial Networks (GANs) is still a developing field using non-Deep Learning-adapted assessment methods. For the purpose of this thesis, a GAN was used as a placeholder for a future, coveted, and highly desirable Deep Learning-based image compression mechanism.

Need a GAN trained on all images, not just popular datasets such as ImageNet or Celeb. Perhaps the next generation ViT needs to be trained on all internet images, or at least a sizable, diverse, and representative subset.

The natural performance limit to the capacity of this model comes from its training sets.

Unique positional encoding can also be achieved using trigonometric representation. For example, a full sentence from text or perhaps a row of pixels from an image could be represented by the various periods of a sinusoid. Thus, the exact location of each token would be unique.

4.2 Optimization

Experiment and change loss functions (MSE was used, can use a GAN specific loss like FID) Learning rate reduction on plateau was used. Most valuable technique, which contributed to the GAN improving its quality of generated image was reducing the learning_rate as the model trains.

Stochastic Gradient Descent (SGD) was used as an optimizer for the GAN.

Perhaps trying Adam could achieve better results on certain types of images, though probably not on average.

Furthermore, experimenting with input image types to cater to what the generative model is best trained on could yield much better results.

Other options to endlessly experiment with include introducing regularization during training such as residual dropout and label smoothing.

Analyze latent space vector with transformer model (not a ViT, but a transformer adaptation) Steer the GAN faster into training to compress Slow computational times

4.3 Present and Future of Image Transformers

4.3.1 Status Quo

Increase in relevant recent publications (13 alone in 2022 thus far) supports the vision of tying vision transformers to image compression.

Status quo of Transformers in Image Processing, Compression, Analysis, and Generation Coveted Deep learning based Image compression In the deep learning/AI evolutionary process, still too early. Models have not been trained on enough image data.

4.3.2 Future Developments

GAN model only trained on finite set (ImageNet, CIFAR-10, Celeb-HQ faces etc) and resolution. Need to train GAN on all images ever.

"TransGAN: Two Pure Transformers Can Make One Strong GAN" [Jiang et al., 2021] NeurIPS 2021

Goal is to replace Generator and Discriminator in a GAN with Transformers free of convolutions. Deterministic, Probabilistic GANs JPEG/MPEG

4.3.3 Training and Costs

Need a ViT on all internet to cost 100M A 512-core TPU v3 pod costs $384/hr to use commercially on GCP. 2.5k core-days means training the ViT cost 24hrs * $384 * 5 of them = $46k. That's for one of many ViT flavors. To train a ViT on the whole TACC Frontera at 20k teraflops (top10) or Stampede at 10k tflops (top25), it would take respectively about a minute and 2 minutes. tpu v3 is 420 teraflops * 2500 = 1M Tflops

(like GPT-3 trained on all internet text, Vision T trained on all google images)

($100M+), GPT-3 cost $10M-$20M r. In terms of image reconstruction on the decoder side, our image reconstructor needs more FLOPs than mbt-m due to the feature aggregation module. In terms of image classification on the decoder side, our image classifier directly performs inference from the compressed features without the image reconstruction process, and thus needs far less computational cost compared with the inference from reconstructed RGB images.

Chapter 5

Summary

This chapter serves to conclude this thesis.

It provides a summary of original contributions made by the author while studying and experimenting with Vision Transformers (ViT) and Neural Image Compression, as well as the broader scientific domains of Machine and Deep Learning and Digital Image Processing.

A summary of key takeaways is provided for the audience.

The author concludes by acknowledging key contributors to the project and serves closing remarks.

5.1 Key Contributions

(experimentation with Vision Transformers, nascent field) The main merit of this thesis was introducing the ViT-Score. A Vision Transformer-Assisted metric for evaluating the performance of a neural image compression, the score correlated with the Generative Adversarial Network verifiably generating a comprehensible image by visual inspection.

The ViT-Score conclusively contributed insights to image quality, relating to human perception of the generated image. The metric can also provide additional insights to understanding the latent space (contextual) preservation of an input image.

This work can be viewed as a stepping stone towards an end-to-end Transformer-based image compression and regeneration.

5.2 Summary

Throughout this report, the reader was presented with all relevant background knowledge necessary to grasp the key contributions listed. A Vision Transformer (ViT) was used to evaluate the capacity of a GAN to compress and generate an image of choice based on object-level similarities with the original input image.

The new metric, referred to as a ViT-Score, was able to capture and assess the quality of the output images and provide valuable insights. The ViT-Score performed well, comparing in capacity to established image quality metrics such as SSIM, MSE, and PSNR.

5.3 Takeaways

The future of image compression technology will be based on a Deep Learning methodology. Due to their generalizability, excellent performance in 1-dimensional data (text), and proven ability to scale to 2-dimensions, Transformers are an excellent choice of architecture to use in image compression and reconstruction.

A Vision Transformer (ViT)-Assisted metric related to image compression can provide additional insights to the latent space (contextual) preservation. Thus, this work can be viewed as a stepping stone towards an end-to-end Transformer-based image compression and regeneration.

Perhaps, such a metric could be used as a Loss function, embedded within the architecture, along with being a useful evaluation metric.

It may cost on the order of $100M and several years, but such a technology will be achieved.

Finally, this image technology can be extended to videos and video compression in further developments.

5.4 Acknowledgments

The author would like to express gratitude towards several individuals and organizations from The University of Texas at Austin campus.

The major inspiration for this project was gathered from two courses taught by the reviewers of this thesis.

EE 371Q, Digital Image Processing taught by Professor Alan C. Bovik was the class where the author learned about Image Compression, Image Quality Assessment, and completed a term project on Generative Adversarial Networks.

CSE 382, Foundations of Machine Learning taught by Professor Rachel A. Ward was the class where the author learned key concepts used throughout this thesis and completed a term project on Vision Transformers (ViT).

Further acknowledgments are made to the Laboratory for Image and Video Engineering (LIVE) at the University of Texas at Austin for providing a source for project inspiration and insights.

Finally, the author would like to express gratitude to The Texas Advanced Computing Center (TACC). TACC provided free access to advanced High-Performance Computing (HPC) resources, which were used throughout the experimentation process in this thesis.

5.5 Closing Remarks

This thesis is written as a graduation requirement for the degree of Master of Science in Computational Science, Engineering, and Mathematics awarded by the Oden Institute at The University of Texas at Austin.

All code has been made available as open source to the general public in the form of a GitHub repository.

Bibliography

Y. Bai, X. Yang, X. Liu, J. Jiang, Y. Wang, X. Ji, and W. Gao. Towards end-to-end image compression and analysis with transformers. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 2022.

J. Brownlee. How to implement the frechet inception distance (fid) for evaluating gans. https://machinelearningmastery.com/how-to-implement-the-frechet-inception-distance-fid-from-scratch/, 2022. Accessed: 2022-04-30.

S.-I. Documentation. Module: metrics - skimage. https://scikit-image.org/docs/stable/api/skimage.metrics.html, 2022. Accessed: 2022-04-30.

A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. *ICLR*, 2021.

M. Ehrlich. The first principles of deep learning and compression, 2022. URL https://arxiv.org/abs/2204.01782.

Google-Research. Vision transformer and mlp-mixer architectures. https://github.com/google-research/vision_transformer, 2022. Accessed: 2022-04-30.

Y. Jiang, S. Chang, and Z. Wang. Transgan: Two pure transformers can make one strong gan, and that can scale up. *Advances in Neural Information Processing Systems*, 34, 2021.

C. Li. Openai's gpt-3 language model: A technical overview. https://lambdalabs.com/blog/demystifying-gpt-3/, 2022. Accessed: 2022-04-30.

A. Mittal, A. K. Moorthy, and A. C. Bovik. No-reference image quality assessment in the spatial domain. *IEEE Transactions on Image Processing*, 21(12):4695–4708, 2012. doi: 10.1109/TIP.2012.2214050.

P. Nayak. Understanding searches better than ever before. https://blog.google/products/search/search-language-understanding-bert/, 2022. Accessed: 2022-04-30.

OpenAI. Dall.e 2. https://openai.com/dall-e-2/, 2022. Accessed: 2022-04-30.

PapersWithCode. An image is worth 16x16 words: Transformers for image recognition at scale. https://paperswithcode.com/paper/an-image-is-worth-16x16-words-transformers-1, 2022a. Accessed: 2022-04-30.

PapersWithCode. Vision transformer explained. https://paperswithcode.com/method/vision-transformer, 2022b. Accessed: 2022-04-30.

Pathmind. A beginner's guide to generative adversarial networks (gans). https://wiki.pathmind.com/generative-adversarial-network-gan, 2022. Accessed: 2022-04-30.

A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. u. Kaiser, and I. Polosukhin. Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc., 2017. URL https://proceedings.neurips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf.

Z. Wang, A. Bovik, H. Sheikh, and E. Simoncelli. Image quality assessment: from error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4):600–612, 2004. doi: 10.1109/TIP.2003.819861.

APPENDIX

5.5.1 Technologies used

Python, PyTorch MATLAB for BRISQUE LaTeX to generate this PDF

5.5.2 GPU, Local machine

NVIDIA GTX 1650Ti CUDA 11

Project dependencies (requirements.txt)

```
kiwisolver==1.3.1
matplotlib==3.2.0
matplotlib-inline==0.1.3
numpy==1.22.3
opencv-python==4.4.0.46
packaging==21.3
pandas==1.4.2
pickleshare==0.7.5
Pillow==8.0.1
pytorch-pretrained-vit==0.0.7
pywin32==303
pyzmq==22.3.0
regex==2020.11.13
scikit-image==0.18.1
scipy==1.5.4
torch==1.7.1+cu110
torchvision==0.8.2+cu110
```

5.5.3 TACC, Stampede2, job submission process

TACC Job submissions

```
#!/bin/bash

#SBATCH -J run_model          # Job name
#SBATCH -o logs/job.%j.out    # Name of stdout output file (%j expands to jobId)
#SBATCH -e logs/job.%j.err    # error file
#SBATCH -p gtx                # Queue name
#SBATCH -N 1                  # Total number of nodes requested (16 cores/node)
#SBATCH -n 1                  # Total number of tasks requested
#SBATCH -t 24:00:00           # Run time (hh:mm:ss) - 24 hours
#SBATCH -A Automatic-Assessment

module load python3
module load cuda/10.0
module load cudnn/7.6.2

cd /work/29369/kliment/
```

```
date

model_path="/model/model.1.pkl"

python3 main.py --data_path ./data/

date
```

TACC srun/idev

```
cd $WORK2
idev -m 30
module load python3

squeue
python3 transformer.py --data_path
```