ABSTRACT
We introduce a new framework for interacting with and manipulate
depth generative models that we call **network bending**. We present a comprehensive set of deterministic transformations that can be inserted as distinct layers into the computational graph of a trained generative neural network and applied during inference. In addition, we present a novel algorithm for clustering features based on their spatial activation maps. This allows features to be grouped together based on spatial similarity in an unsupervised fashion. This results in the meaningful manipulation of sets of features that correspond to the generation of a broad array of semantically significant aspects of the generated images. We demonstrate these transformations on the official pre-trained StyleGAN2 model trained on the FFHQ dataset [17]. In doing so, we lay the groundwork for future interactive multimedia systems where the inner representation of deep generative models are manipulated for greater creative expression, whilst also increasing our understanding of how such “black-box systems” can be more meaningfully interpreted.

CCS CONCEPTS
- Computing methodologies → Neural networks; Image processing.

KEYWORDS
neural networks, generative models, manipulation, expressivity, interpretability

1 INTRODUCTION
Generative models, such as Generative Adversarial Networks (GAN) have come a long way in recent years. They can for example produce attractive high-resolution, highly realistic images of nearly any objects or persons. Efforts have also been made to produce tools to better manipulate the results. These often take the form of finding ways of navigating the latent space [23], or finding component vectors that represent key semantic properties [12, 27, 29], or trying to map out the latent space to find interpolations that map to semantic properties [15]. However, navigating the latent space is difficult, as it is high dimensional, with non-intuitive information and thus extremely difficult to comprehend fully. Evolutionary interfaces [30] and other graphical user interfaces have been built to operate on components of the latent space [19] but these do not allow the user to customise their effects and generate images that sit completely outside the data distribution modelled by the generative network. It may be possible to find unusual samples, but these tend to be at the boundaries between classes or are sampled from areas of the latent space that are not well represented and thus difficult to obtain otherwise than by chance.

Manipulating the inner representations of a neural network gives a potentially powerful alternative method to operate in a deterministic way. The goal would be to give the user the ability to interact with pre-trained generative models to produce samples outside the data distribution in an intuitive way, i.e. under the direct hand of the user. There has been few works on this front, and they have been limited to the ablation of pre-specified individual features corresponding to the generation of semantically meaningful objects [4, 6], or to ‘painting’ on the activation maps of said features [2]. Such techniques limit the user to only manipulate a small number of pre-selected features, representing a small proportion of all available filters, and with limited modes of interaction.

In this work we introduce a new approach to manipulating generative models that we call **network bending**. We have implemented a wide array of image filters that can be inserted into the network and applied to any assortment of features, in any layer, in any order.
We use a plug-in architecture to dynamically insert these filters as individual layers inside the computational graph of the pre-trained network, ensuring efficiency and minimal dependencies. We also present a novel approach to grouping together features in each layer. This is based on spatial similarity to reduce the dimensionality of the parameters that need to be configured by the user, providing a visual understanding of how groups of features combine to produce different aspects of the image. We show results from these processes and map out a pipeline to harness the generative capacity of GANs in producing novel and expressive images.

2 BACKGROUND

2.1 Deep Generative Models
A generative model is the application of machine learning to learn a configuration of parameters that can approximately model a given data distribution. This was historically a very difficult problem, especially for domains of high data dimensionality such as for audio and images, but with the advent of deep learning and deep generative models, great advances were made in the last decade. Deep neural networks are now capable of generating realistic sounding audio [9, 25] and images [7, 17, 18]. In the context of generating images, Variational Autoencoders [20, 28] and Generative Adversarial Networks or GANs [13] have been major breakthroughs that provide powerful methods for training generative models. Over the past few years there has been major improvements to their fidelity and training stability, with application of convolutional architecture [27], progressively growing architecture [16] leading to the current state of the art in producing unconditional photo-realistic samples StyleGAN [17] and the later improved StyleGAN2 [18].

2.2 Interpretability of Neural Networks
Developing methods for understanding the purpose of the internal features (aka hidden units) of deep neural networks has been an ongoing area of research. In computer vision and image processing applications, there have been a number of approaches, such as through visualisation, either by sampling patches that maximise the activation of hidden units [34, 36], or by using variations of backpropagation to generate salient image features [24, 31, 34]. A more sophisticated approach is network dissection [4] where units responsible for the detection of semantic properties are identified by analysing the responses of hidden units to semantic concepts and quantifying the alignment of hidden units to semantic properties.

Network dissection was later adapted and applied to generative models [4], by removing individual units, while using in combination a bounding box detector [33] trained on the ADE20K Scene dataset [37]. This led to the ability to identify a number of units associated with the generating of certain aspects of the scene. This approach has since be adapted for music generation [6]. A new interactive interface building on this approach was presented with the GANPaint framework [2], allowing users to ‘paint’ onto the activation maps of said features in order to edit and control the spatial formation of specific features generated by the GAN.

2.3 Metric Learning
Metric learning is the application of machine learning to learn a metric about a given data domain where the distances between encodings of samples can be measured and used to infer their degree of similarity [21]. Producing a task specific distance metric can then be used to perform other tasks, such as classification, clustering or information retrieval.

3 PROPOSED TRANSFORMATION LAYERS
We have implemented a broad variety of deterministically controlled transformation layers that can be dynamically inserted into the computational graph of the generative model. The transformation layers are implemented natively in PyTorch [26] for speed and efficiency. We treat the activation maps of each feature of the generative model as a 1-channel image, and apply simple transformations to those activation maps before they are fed to the next layer of the network. The transformation layers can be applied to all the features in a layer, or a random selection, or by using pre-defined groups automatically determined based on spatial similarity of the activation maps (Section 4).

3.1 Numerical Transformations
We begin with simple numerical transformations $f(x)$ that are applied to individual activation units $x$. We have implemented four distinct numerical transformations: the first is ablation, which can be interpreted as $f(x) = x \cdot 0$. The second is inversion, which is implemented as $f(x) = 1 - x$. The third is multiplication by a scalar $p$ implemented as $f(x) = x \cdot p$. The final transformation is binary thresholding (often referred to as posterisation) with threshold $t$, such that:

$$f(x) = \begin{cases} 1, & \text{if } x \geq t \\ 0, & \text{otherwise} \end{cases}$$

(1)

3.2 Affine Transformations
For the set of transformations we treat each activation map $X$ for feature $f$ as an individual matrix, that simple affine transformations can be applied too. The first two are horizontal and vertical reflections that are defined as:

$$X = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad X = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

(2)

The second is translations by parameters $p_x$ and $p_y$ such that:

$$X = \begin{bmatrix} 1 & 0 & p_x \\ 0 & 1 & p_y \\ 0 & 0 & 1 \end{bmatrix}$$

(3)

The third is scaling by parameters $k_x$ and $k_y$ such that:

$$X = \begin{bmatrix} k_x & 0 & 0 \\ 0 & k_y & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

(4)

Note that in this paper we only report on using uniform scalings, such that $k_x = k_y$. Finally, fourth is rotation by an angle $\theta$ such that:

$$X = \begin{bmatrix} \cos(\theta) & -\sin(\theta) & 0 \\ \sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

(5)

A comparison of these affine transformations being applied to all the activation maps in a single layer can be seen in Figure 1. Other
affine transformations can easily be implemented by designing the matrices accordingly.

3.3 Morphological Transformations

We have implemented two of the possible basic mathematical morphological transformation layers, performing erosion and dilation \([32]\) when applied to grayscale activation maps. These can be configured with the parameter \(r\) which is the radius for a circular kernel (aka structural element) used in the morphological transformations. Examples of these transformations applied to activation maps can be seen in Figure 2.

Figure 2: Examples of morphological transformations being applied to two individual activation maps (top and bottom row) in Layer 10. Left: unmodified activation maps. Middle: activation maps after erosion was applied \((r = 2\) pixels). Right: activation maps after dilation was applied \((r = 2\) pixels). All activation maps have been normalised into a grayscale image space.

4 CLUSTERING FEATURES

As most of the layers in current state of the art GANs, such as StyleGAN2, have very large numbers of convolutional features, controlling each one individually would be far too complicated if one were to build a user interface around this kind of manipulation. In addition, because of the redundancy existing in these models, manipulating individual features does not normally produce any kind of meaningful outcome. Therefore, it is necessary to find some way of grouping them together into more manageable ensembles of sets of features. Ideally, such sets of features would correspond to the generation of distinct, semantically meaningful, aspects of the image and manipulating each set would correspond to the manipulation of specific semantic properties in the resulting generated sample. In order to achieve this, we present a novel approach, combining metric learning and a clustering algorithm to group sets of features in each layer based on the spatial similarity of their activation maps. We train a separate convolutional neural network (CNN) for each layer of the StyleGAN2 model with a bottleneck architecture (first introduced by \([14]\)) to learn a highly compressed feature representation, which is then used in combination with the k-means clustering algorithm \([8, 22]\) to group sets of features in an unsupervised fashion.

4.1 Architecture

Figure 3: Diagram of the adaptive architecture for the CNNs used to perform metric learning followed by feature clustering. For every layer of the GAN we train a CNN with adaptive depth depending on input dimensions. Following the convolutional layers the information is funneled through a narrow bottleneck \(\mathbb{R}^{10}\) before being expanded back to the number of features present in that layer for softmax classification. After training the feature vector \(\tilde{v}\) from the bottleneck is used for k-means clustering. Top-right: Diagram of the architecture used in layers 3 & 4. Underneath: Diagram of the architecture used in layers 9 & 10. See 1 for details on input resolution, depth and number of features learned for each layer.

For each layer of the StyleGAN2 model, we train a separate CNN on the activation maps of all the convolutional features. As the resolution of the activation maps and number of features varies for the different layers of the model (a breakdown of which can be seen in Table 1) we employ an architecture that can dynamically be changed, by increasing the number of convolutional blocks, depending on what depth is required (Figure 3).

We employ the ShuffleNet architecture \([35]\) for the convolutional blocks in the network, which is one of the state of the art architectures for efficient inference (memory and speed) in computer vision applications. For each convolutional block we utilise a feature depth of 50 and have one residual block per layer. The motivating factor in many of the decisions made for the architecture was not achieving the best accuracy per se, but having a network that can learn a sufficiently good metric while also being reasonable quick to train (all 16 models) and quick and lightweight enough that it could be used in a real-time setting where clusters could quickly be calculated for an individual latent encoding.

After the convolutional blocks, we flatten the final layer (4x4x50) and learn from it a mapping into a narrow bottleneck \((\tilde{v} \in \mathbb{R}^{10})\), before re-expanding the dimensionality of the final layer to the number of convolutional features present in the GAN layer. The goal of this bottleneck is to force the network to learn a highly compressed feature representation of the different convolutional features in the GAN. While this invariably looses some information, most likely negatively affecting classification performance.
We generated a training set of the activations of every feature for vector from the bottleneck, giving a more compressed feature representation than what standard softmax feature learning would offer. And feeding the activation maps to the layers being trained. But is used as a feature vector where the distances between points can be used to find a general purpose set of clusters.

The clustering algorithm for a single example is activated by a forward pass of the GAN performed without any additional transformation layers being inserted, this to obtain the unmodified activation maps. The activation map $X_{df}$ for each layer $d$ and feature $f$ is fed into the CNN metric learning model for that layer $C_{df}$ to get the feature vector $\tilde{v}_{df}$. The feature vectors for each layer are then aggregated and fed to the k-means clustering algorithm — using the Lloyd’s method [22] with Forgy initialization [8, 11]. This results in a pre-defined number of clusters for each layer. Sets of features for each layer can then be manipulated in tandem by the user.

Alternatively, to find a general purpose set of clusters, we first calculate the mean feature vector $\bar{v}_{df}$ that describes the spatial activation map for each convolutional feature in each layer of StyleGAN2 from a set of $N$ randomly generated samples — the results in the paper are from processing 1000 samples. Then we perform the same clustering algorithm as previously for individual samples on the mean feature vectors. The mean vector feature representations are calculated using the formula:

$$\bar{v}_{df} = \frac{1}{N} \sum_{n=1}^{N} v_{dfn}$$

The clustering algorithm for our code on an unofficial PyTorch implementation, where the official TensorFlow weights have been converted into a format suitable for use in PyTorch: https://github.com/rosinality/stylegan2-pytorch

The source code for this work and links to additional materials can be found at: https://github.com/terencebroad/network-bending

## 4.3 Clustering Algorithm

Once the CNN’s for every layers have been trained, they can then be used to extract feature representations of the activation maps of the different convolutional features corresponding to each individual layer of the GAN. There are two approaches to this. The first is to perform the clustering on-the-fly for a specific latent for one sample. A user would want to do this to get customised control of a specific sample, such as a latent that has been found to produce the closest possible reproduction of a specific person [1, 18]. The second approach is to perform clustering based on an average of features’ embedding drawn from many random samples, which can be used to extract feature representations of the activation maps of the different convolutional features corresponding to each individual layer of the GAN.

### 4.2 Training

We generated a training set of the activations of every feature for every layer of a 1000 randomly sampled images, and a test set of 100 samples. In theory training could be done continuously by sampling random latent vectors, passing them through the GAN and feeding the activation maps to the layers being trained. But for efficiency during training, as well as for providing results being reproducible and allow future comparison of methods, we opted to generate a fixed training and test set (that we have made publicly available).1

We trained each CNN using the softmax feature learning approach [10], one of the most straightforward and reliable methods for distance metric learning. This method employs the standard softmax training regime [5] for CNN classifiers. After training the softmax layer is discarded and the embedding of the final layer is used as a feature vector where the distances between points in feature space permit to gauge the degree of similarity of two samples. The one difference in our approach to standard softmax feature learning is that we use the second to last layer, the feature vector from the bottleneck, giving a more compressed feature representation than what standard softmax feature learning would offer.

During training, this is in-fact the desired result. We want to force the CNN to combine features of the activation maps with similar spatial characteristics so that they can easily be grouped together by the clustering algorithm. Another motivating factor is that the clustering algorithm we have chosen (k-means) does not scale well for feature spaces with high dimensionality.

### 5 RESULTS

We demonstrate the results of applying transformations to entire layers and individual clusters applied to the official StyleGAN2 model weights, that was trained on the Flickr-Faces-HQ (FFHQ) dataset.² It is possible to produce a vast array of different visual results by applying different transformations to different sets of features in different layers. In this paper we are only able to share a small sample of these, but a larger selection of results, as well as the code and the models used to calculate the clusters will also be made publicly available.³

#### 5.1 Transforming Clustered Feature Sets

We found out experimentally that sets of features that are responsible for the generation of certain semantic features in the generated results emerge from the clusters calculated with the average features of 1000 samples. Examples include the generation of eyes and nose (Figure 4). Such clustered feature sets can be manipulated

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1See footnote 3.

2We base the implementation of our code on an unofficial PyTorch implementation, where the official TensorFlow weights have been converted into a format suitable for use in PyTorch: https://github.com/rosinality/stylegan2-pytorch

3The source code for this work and links to additional materials can be found at: https://github.com/terencebroad/network-bending

| Layer | Resolution | #features | CNN depth | #clusters |
|-------|------------|-----------|-----------|-----------|
| 1     | 8x8        | 512       | 1         | 5         |
| 2     | 8x8        | 512       | 1         | 5         |
| 3     | 16x16      | 512       | 2         | 5         |
| 4     | 16x16      | 512       | 2         | 5         |
| 5     | 32x32      | 512       | 3         | 5         |
| 6     | 32x32      | 512       | 3         | 5         |
| 7     | 64x64      | 512       | 4         | 5         |
| 8     | 64x64      | 512       | 4         | 5         |
| 9     | 128x128    | 256       | 5         | 4         |
| 10    | 128x128    | 256       | 5         | 4         |
| 11    | 256x256    | 128       | 6         | 4         |
| 12    | 256x256    | 128       | 6         | 4         |
| 13    | 512x512    | 64        | 7         | 3         |
| 14    | 512x512    | 64        | 7         | 3         |
| 15    | 1024x1024  | 32        | 8         | 3         |
| 16    | 1024x1024  | 32        | 8         | 3         |

Table 1: Table showing resolution, number of features of each layer, the number of ShuffleNet [35] convolutional blocks for each CNN model used for metric learning and the number of clusters calculated for each layer using k-means.
results usually map to what would be intuitively predicted, for example what resizing a person’s eyes should look like. However, some counter-intuitive and unexpected results may also occur.

Not only do we find clusters responsible for the generation of semantically meaningful attributes, such as the sensory organs of the face (Figure 4), but in other layers we find clusters that are responsible for the generation of a multitude of characteristics of the image. In the higher layers (especially the third layer) the clusters are responsible for the spatial formations of facial features and other aspects of the image. In the lower layers, we find clusters of features responsible for properties such as: highlights, textures, the formation of edges, colour balance and saturation (Figure 5).

5.2 Chaining Transformations

Applying individual transformations to individual layers or individual clusters of features can be interesting from the perspective of neural network interpretability. In particular, this process can give insights into how the network generates images; furthermore, it can also produce some surprising and highly stylised results. However, from the perspective of building tools that impact the generation of expressive and novel samples, doing so one transformation at a time can be quite restricting. But note that with our approach, we are not limited in this manner, and a user can explore more complicated effects by chaining multiple transformations. In Figure 6 a few examples of combining multiple transformations when applied to different sets of features on different layers, illustrate how our proposed architecture can generate very unusual and highly distinctive results.
6 DISCUSSION
The results we have presented show that our methods can produce a wide variety of different visual and aesthetic outcomes. These methods can also provide an insight into how GANs produce such realistic images in the first place, showing how different sets of features combine to produce different aspects of the image. In the following we discuss some of the relevant issues in greater detail.

6.1 Neural Network Interpretability
Our results demonstrate that sets of features, not individual features, should be looked at in order to understand how generative models produce different aspects of the image. This is in contrast to previous approaches [3, 4] that only interrogate the function of individual features, which we argue is not capable of capturing a full account of how the network generates results as the networks tend to be robust to the transformation of individual features.

We also show that sets of features, which may not be particularly responsive to certain transformations, are very responsive to others. Figure 7 shows a cluster of features, that when ablated, has little noticeable effect on the result, but when another transformation is applied to that cluster, the changes to the generated results are significant. This, we argue, shows that the functionality of features, or sets of features, cannot be understood only through ablation [4] because of the high levels of redundancy present in the learned network parameters. We show that their functionality can be better understood by applying a wide range of deterministic transformations, of which different transformations are better suited to revealing the utility of different sets of features (Figures 4 & 5).

Finally our method is completely unsupervised, and does not rely on auxiliary models trained on large labelled datasets [4] or other kinds of domain specific knowledge. This approach therefore can be applied to any CNN based GAN architecture used for image generation which has been trained on any dataset.

6.2 Expressivity
From the perspective of producing novel, expressive outcomes, we advance that we have introduced an important new approach to the experimentation with, and manipulation of, deep generative models. One common criticism of using deep generative models in the creation multimedia artifacts, is that they can only re-produce samples that fit the distribution of samples in the training set. However, by introducing deterministic controlled filters into the computation graph during inference, these models can be used to produce a large array of novel results. We submit that such outcomes could not reasonably be produced using any other existing method of image manipulation or generation. The results we have obtained markedly lie outside the distribution of training images, or indeed in some cases, of any images that have ever been produced before.

6.3 Limitations
While we have been able, in an unsupervised fashion, to extract sets of features that represent the generation of semantically meaningful components of the image, we have not done a comparative analysis of: different methods of metric learning, different architectures used for feature extraction, different algorithms for clustering or different numbers of clusters defined for each layer. We plan to do a more thorough analysis of all of these aspects in future work, but we are of the opinion that the results we have presented are already significant. Furthermore, they map out a blueprint for future systems that utilise this kind of pipeline for ascertaining sets of features and using them for the manipulation of generative models by transforming them in conjunction with deterministic controlled transformation layers.

We have made a number of assumptions that have guided architectural and design choices, with the view on what would be suitable for an interactive multimedia system, in particular with respect to the complexity of the potential parameter space. However, as we have not yet integrated this system with a user interface, we have not been able to test these assumptions. Further work will be required to design, test and refine such an interface. We also anticipate that more efforts will be necessary to visualise sets of activation maps and the transformations applied to them, this to give a better understanding of how such transformations are affecting the internal state of the model.

7 CONCLUSION
In this paper we have introduced a novel approach for the interaction with and manipulation of deep generative models that we call network bending. By inserting deterministic filters inside the network, we present a framework for performing manipulation inside the networks’ black-box and utilise it to generate samples that have no resemblance to the training data, or anything that could be created easily using conventional media editing software. We also present a novel clustering algorithm that is able to group sets of features, in an unsupervised fashion, based on spatial similarity of their activation maps. Demonstrating that this method is capable of finding sets of features that correspond to the generation of a broad array of semantically significant aspects of the generated images. Thus providing a more manageable number of sets of features that a user could interact with.

It is important to note we are not manipulating individual samples, but altering the computational graph of the system that generates the sample. Therefore, the same effect can be applied across the whole distribution of potential generated samples with negligible overhead in performance cost compared to regular inference.
We propose that using our approach, possibly in conjunction with other methods, for a better understanding and navigating of the latent space of a model can provide a very powerful set of tools in the creation of novel multimedia artifacts. While we have only demonstrated these methods on deep generative models for images, we expect that our methods — with the implementation of suitable domain specific transformations — could easily be applied to other domains, including audio, video or text generation.

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