## Abstract:

Generative Adversarial Networks (GANs) are rapidly becoming more and more prevalent in today's world, seeing increased use in many fields and creating many complications for lawmakers. GANs use machine learning in order to learn how to generate new and original data based on the data used to train it. The intention of this project is to use a GAN that can generate pixel art sword sprites that are capable of being used in a video game. Swords have been chosen due to the availability of training data although future work would see the list of items generated expanded. The images will be evaluated primarily based on the shape of the sword, this will mean the sprite must look like the item that is being created, the blade, hand guard and handle will be specifically be looked for and the image should look crisp with as little to no artifacting in the image. Additionally, these images will be generated in the context of a fantasy video game this will allow for a greater degree of flexibility when judging the practicality of the sword however it will also allow for more creative and versatile designs. Although, the shape of the image is the most important fonter that the sprites will be judged on, they will however also be evaluated based on artistic design this will include colour and whether fantastical elements have been included such as flames. This will likely cause an interesting balancing act as more fantastical elements may cause designs to lose the intended shape.


## Research:

Pioneered by Ian Goodfellow in 2014 (Giles, 2018) GANs make use of two networks, a generator and a discriminator, working in competition with each other. There have been several variations of GANs specialising in different purposes however the roles of the discriminator and generator have largely remained the same. The discriminator is fed both fake data that has been created by the generator and real data from the data set. Its job is to correctly identify the forgeries and the genuine articles from the dataset and its success rate is determined by the percentage of the guesses that are correct. The generator however, does not have access to the real data, instead it learns through the feedback provided by the discriminator based on the success of the forgeries it has created. (Creswell et al., 2018)

GANs can be used to impersonate specific peoples voices or faces this can have a huge effect on many parts of life some of the significant negative effects including undermining evidence in legal cases as a result of fake ‘evidence’ being created or real evidence not being believed due to the possibility that it is fake. (Yang et al., 2018) However, the application of GANs does not always have malicious uses. The ability to mimic or alter images and sounds can have a great effect in films, some applications would include updating older films to modern standards by increasing resolution or converting black and white into colour.(M, 2020) The application of GANs is extremely wide and due to its creative nature its effect whether positive or negative relies heavily on how it is applied.

An application that is particularly interesting in the field of video games is in level generation where a GAN struggles to produce environments that are both appealing and playable. Various attempts have been made to solve this issue such as the work done by Ruben Torrado which attempts to design a new architecture style that is better suited to solving this issue. (Torrado et al., 2019)

Another application of GANs is the ability to create unique works of art. This can have many applications that might not seem obvious at first such as that art could be generated using images of a specific artist and then sold as genuine works from that person due to being in the same style. However, generating art can have many positive effects too such as being used in the design industry for creating prototype designs or in video games for creating sprites or icons.(salian, 2020)

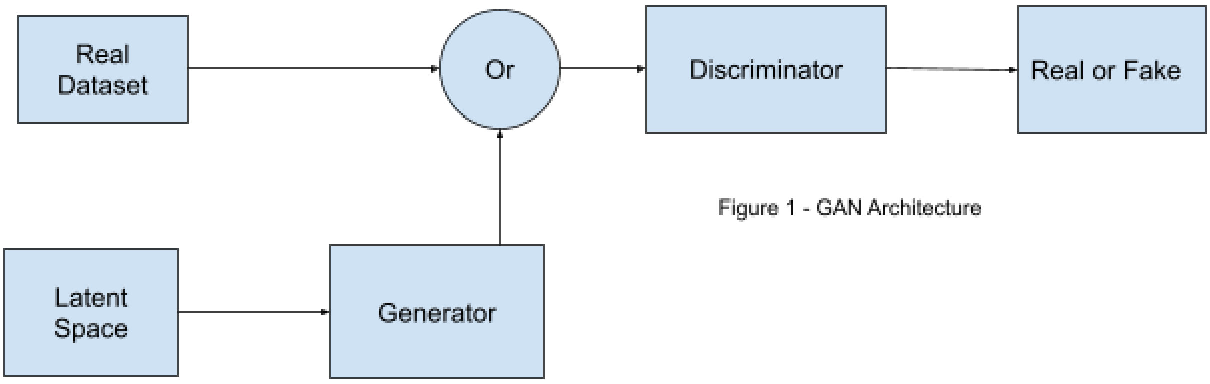


Figure 1 - GAN Architecture

**Technical Implementation:**

Collating the dataset for this project began by searching through google images in the hopes of scraping pixel art images however many results were unsuitable due to the varying styles of pixel art. This led the search to various pixel art dedicated websites where users can upload their work this meant the varying styles of pixel art could be quickly filtered. All images collected for this dataset were 32x32 bit pixel art; this prevented any cropping and resizing issue occurring and kept the pixel art images in a similar style.

DCGAN

To start the project the DCGAN architecture was used, figure 2 shows the final result from the DCGAN. This GAN ran for 800 epochs, when experimenting with this number 800 seemed to be an optimal point as increasing the number no longer had a positive effect on the quality of the images, instead producing more images of a similar nature, and reducing this number lead to a greater amount of artifacting and blurry results. Similar experimentation was done with the learning rate value; the final results were performed using a learning rate of 0.0003, however values ranging from 0.02 and 0.00005 were used which produced worse results or required vastly increased time for similar outcomes. While working with the DCGAN the dataset had many alterations, most noticeably was the expansion of the dataset size as more data was needed to produce a solid sword shape. However, in order to get the best shape the images

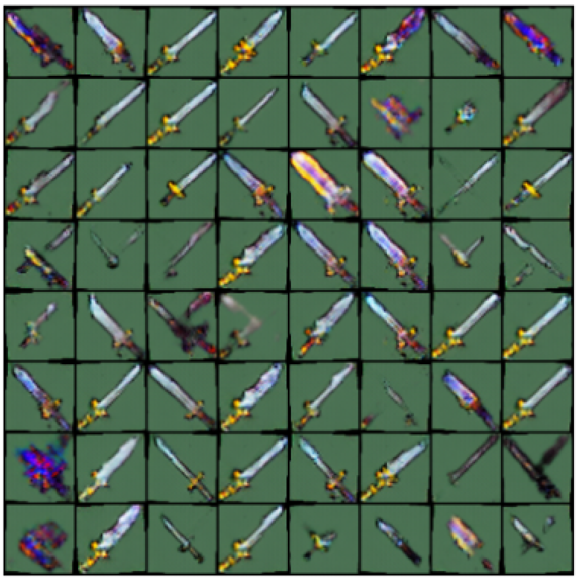

Figure 2 - DCGAN

included in the data set had to be carefully selected this meant removing many of the images with less typical designs which reduced the dataset from nearly 500 to 360. After refining the dataset the DCGAN was largely capable of producing images with the general shape of a pixel art sword however these images suffered a great deal of artifacting, creating very blurry images with a messy blend of colours used not resembling anything designed by an artist. Additionally, the results show many repetitions of very similar images which would suggest the training data is not large enough to get the desired result.

Overall the DCGAN did not frequently if ever produce results that could be used in a video game. However, it was useful in identifying early issues with the dataset and allowed for a faster refinement of the images that had been collected.

StyleGAN

In order to get improved results a bigger dataset was needed however collecting more images manually was not feasible as such StyleGAN with a pretrained neural network has been used, allowing for some of the benefits of a large dataset while using the collated images to specialise the model for creating pixel art swords, this is a form of transfer learning.
When using StyleGAN the base pretrained model, used to train from, had an important noticeable effect on the end result. Figure 3 and figure 4 show the generated results trained for a similar amount of time and where the only other difference is the pretrained model used as the starting point. Figure 3 shows the results from a model using the pretrained clipart model(art model) and figure 4 shows a model trained using a pretrained network of doors(door model). It is possible to see in the results that the art model has a slightly increased variation of colours such as blues and reds, softer edges and is less likely to have a clearly discernible sword shape. Whereas, the door model has a more solid sword shape, less artifacting but also more bland colours with greys and browns being more common. Although other pretrained models were tested and some provided some positives, such as the increased colour of the art model, the door pretrained model was primarily used due to the increased likelihood of producing usable sword images.

Figure 3 - Clipart Model

Figure 4 - Door Model

While working with the StyleGAN the dataset saw more refinement. Unexpectedly, during this process more images in the dataset did not necessarily produce better generated images compared to a smaller dataset that had more varied images. In order to make the most of this, the dataset was refined to only include a few images by a single artist this provided a dataset with a lot of variation between designs however due to not having enough data the shape started to suffer this led to a balancing act between having enough data and getting the most variation. Additionally, a current issue of the dataset is the lack of variation in vertical oriented swords as this is causing the majority of vertical swords that are generated to look very similar, given more time the dataset would be expanded to include a greater variation of swords drawn vertically or find adequate replacements for these swords drawn at a diagonal like the rest of the dataset. However, it was found that including these images helped ensure the blade, guard and handle were distinct in the generated designs.

**Results & Conclusions:**

The final results with the StyleGAN have produced images with very good shape over all, however the images do still have some issue with artifacting or producing results that are incomplete, this should be solved with more training. Additionally, the final designs, which can be seen in figure 5 are quite varied with very few identical designs however the designs are quite 'safe' with a lack of fantastical elements and as this project has been done in the context of a fantasy video game this is a drawback. To solve this issue it is likely that more designs with fantastical elements such as flaming blades or designs such as wings should be included with greater frequency in the dataset, this was however difficult due to the lack of suitable designs during data collection. The dataset for the final results contained 191 images. However, it is likely that more images would have been useful as other testing found that just over 200 images gave a more optimal balance of variation in design with sword shape. Future work would see the dataset recollated given the new knowledge of what would improve the designs and expanding upon the number of items that could be generated by the network, examples could be other pixel weapons, or armour, miscellaneous items such as tables and chairs, and environmental art such as trees this would allow for a full pixel art fantasy game to be developed using art generated from a GAN.

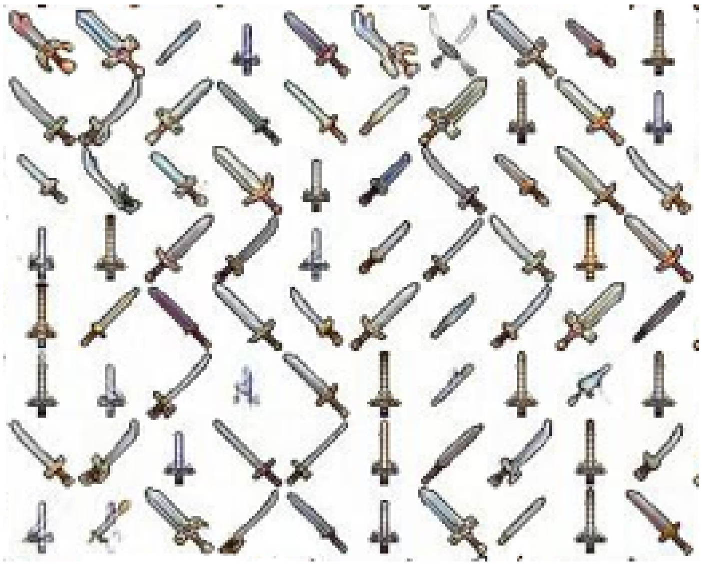
Figure 5 - Final Results

**Reference:**

Creswell, A., White, T., Dumoulin, V., Arulkumaran, K., Sengupta, B. and Bharath, A.A. (2018) Generative Adversarial Networks: An Overview. *IEEE Signal Processing Magazine*. 35 (1), pp. 53–65. doi:10.1109/msp.2017.2765202 [Accessed 12 November 2019].

Yang, G., Singh, R., Raj, B. (2018) Voice Impersonation using Generative Adversarial Networks. Accessed from: https://arxiv.org/abs/1802.06840[19/01/2022]

M, N. (2020) *Media and entertainment sector-specific GAN applications*. Available from: https://medium.com/analytics-vidhya/media-and-entertainment-sector-specific-gan-applications-d0ce42cd9b92 [Accessed 22 January 2022].

Torrado, R., Khalifa, A., Green, M., Justesen, N., Risi, S., Togelius, J. (2019) Bootstrapping Conditional GANs for Video Game Level Generation. New York University.

salian (2020) *Generating Art with GANs*. Available from: https://blog.jovian.ai/generating-art-with-gans-352ceef3d51f [Accessed 22 January 2022].

Giles, M. (2018) *The GANfather: The man who's given machines the gift of imagination*. Available from: https://www.technologyreview.com/2018/02/21/145289/the-ganfather-the-man-whos-given-machines-the-gift-of-imagination/.