Hello, my name is Muhammad Saad bin Sagheer. In this tutorial, I will discuss about one of the major challenges in generative adversarial networks which is called mode collapse. We will discuss about why it happens; it affects on generated outputs and some of the techniques to mitigate it. Now let's get started with the slides. I hope my screen is visible right now. It will be visible right now. Just a second.

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So this is the agenda for presentation. Let me, yeah. So we'll discuss about GAN, its objective function, mode collapse, and some of the causes and mitigation strategies to address this issue. So before starting, let's first discuss what GAN is. A GAN consists of two neural networks, a generator and a discriminator.

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They both compete in an adversarial setup. The generator tries to create realistic samples while the discriminator evaluates whether a sample is real or fake as seen in this image. Some of the real data is shown to the discriminator and some of the fake data, the discriminator try to distinguish between them. So now discussing about the

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objective function the discriminator first of all tries to maximize so its role is it is denoted by d and it has one objective to correctly distinguish between real data from fake data it aims is to maximize the function by ensuring that for real data x the output d of x is close to one meaning the sample is classified as real for fake data it will be close to zero

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and it will be classified as fake. In simple terms, the discriminator wants to separate real data from fake as accurately as possible, while the generator's goal is to minimize this function. So, by generating fake data that fools the discriminator,

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The G has the opposite objective. Instead of maximizing the function, it tries to minimize it. So by generating fake data, it fools the discriminator, making D of G of Z as close to 1 as possible. This creates a competitive game between G and D, driving G to produce

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realistic data. So in this example, we can see that the generator goal is to maximize this function. So now discussing about what a model collapse is. So it occurs when the generator fails to generate diverse outputs. Instead of covering the full distribution of real data, it only produces a limited set of samples.

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this leads to poor quality results and a lack of variation in generated outputs instead of realistic faces or for example in this case the numbers one to nine or zero to nine should be shown but here on the left hand side only 300 is shown and on the right hand side only eight is shown so this is not covering the overall diversity of the data it is only showing some numbers so it means that it may it is affected from more collapse

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So now discussing about why it happens. The first of the reason is unstable training. These gains rely on adversarial learning which is inherently unstable. If the balance between generator and discriminator is off, more collapse may occur. The second reason is overpowering discriminator. If the discriminator becomes too strong, the generator struggles to learn and start producing

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repetitive outputs. The third reason is poor generator updates. If the generator updates do not capture enough diversity, it converges to a small set of samples instead of exploring the full distribution of data. And the last reason is high learning rate. At high learning rate, it can cause abrupt updates leading to unstable behavior.

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So the generator tries to stick to a few modes rather than landing the full distribution. So these are the causes for model collapse. Now discussing about the solution. First one is mini-band distribution. So instead of evaluating samples individually, the discriminator accesses groups of samples at once. This encourages the generator to produce more diverse outputs as it needs to generate samples that

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vary within a mini batch as shown in this function. So it is capturing the overall groups of samples at one place and then it sums them all. The second solution is mini feature matching. Feature matching is another technique instead of simply

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For trying to fool a discriminator, the generator is trained to match the statistical feature of the real data in an intermediate layer of the discriminator. So they are introducing an intermediate layer in the real discriminator. This forces the generator to create samples that are more representative of the overall data distribution, rather than sticking to the repeated patterns.

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The third solution is Unrolled GANs. It modifies the discriminator behavior to make training more stable. Instead of updating the discriminator, immediately after a generator update, it looks ahead multiple training steps before providing feedback. This prevents the generator from collapsing into a repetitive pattern and improves its learning. So it will look ahead some of the steps and then it will update it.

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The second, the last solution is the weather stream GAN or WGAN. It uses Earth's mover distance instead of traditional loss functions and leads to more stable and prevents mode collapse. It leads to more stable training and prevents mode collapse. So these are the reasons and some of the strategies to mitigate it. The first advantage of implementing this strategy is

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improved quality and diversity of generated samples. When a GAN suffers from more collapse, it tends to generate highly similar or even identical outputs, failing to capture the full diversity of that data. By addressing this issue, we ensure that the model generates a variety of high-quality samples that better represent the underlying data distributions.

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The second advantage is its ability to learn complex data distributions. A wide dataset will cover all the diverse and all the statistics of the data instead of just repetitive some of the learned samples. The third advantage is its increased stability and reliability.

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So addressing model collapse leads to more stable and reliable gan training and stability in gan is a common issue due to the adversarial nature of training. When the more collapse is prevented, the generator and the simulator improve together leading to a more balanced and effective learning process. So one of the disadvantages of model collapse is higher computation and training cost.

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These techniques like a mini batch distribution and all the techniques we have learned, they require additional computations. This increases both training time and memory usage. And the second reason is, and the second of the disadvantages is the risk of overfitting. forcing them to capture more diverse set of patterns we sometimes risk our fitting of the training data this can reduce the model's ability to generalize to unseen samples when the when the unseen samples come the model the model does not capture the full diversity of the data and also it is more difficult to train due to its increased complexity and also it is prone to adversarial attacks so now we come to the code

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We have the data set and some of the pre data processing techniques which I am not going to cover. The data set is the cipher 10 data set. We have defined the generator, discriminator and the mitigation functions. Then we have trained our model first on without mitigation function and then after applying mitigation. We can see that after mitigation, the dataset has captured more diverse functionalities of the data rather than before when it has captured some of the features of the dataset.

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So we can clearly see what are the benefits of applying mitigation strategies. So that's it for this presentation. Thank you very much.