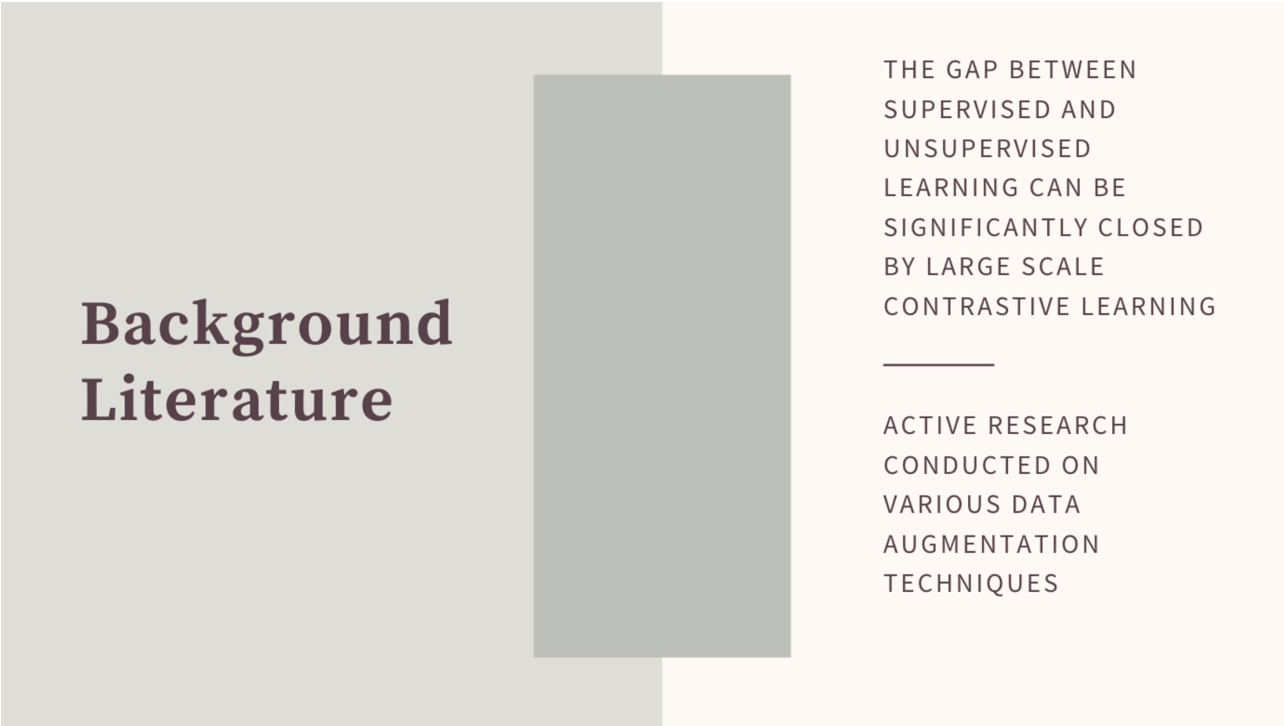
Presentation Transcription

Slide 1:

Hello everyone, my name is Raahim. Today, me and my team member Harum will be presenting the ICLR 2021 paper, Training GANs with stronger augmentations via contrastive discriminator. So let's start!

Time - 11 seconds

Slide 2:



There has been recent research and advancements in contrastive learning which indicated that the performance gap between supervised and unsupervised learning can be greatly improved using contrastive learning over strong data augmentations. In this regard, there has also been some recent works revolving around various data augmentation techniques aiming to prevent discriminator overfitting and ultimately stabilize GAN training.

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Slide 3:

Although there have been active research revolving around data augmentation, those researches included only a limited set of augmentations such as flipping and spatial translation. Furthermore, it is still a question as to which augmentations are good for GANs and the ones which would lead to stable GAN training. Lastly, augmentations for contrastive learning that can efficiently keep information relevant to downstream tasks such as classification also is a challenging question which if effectively answered will be able to extract the mutual information shared across augmentations.

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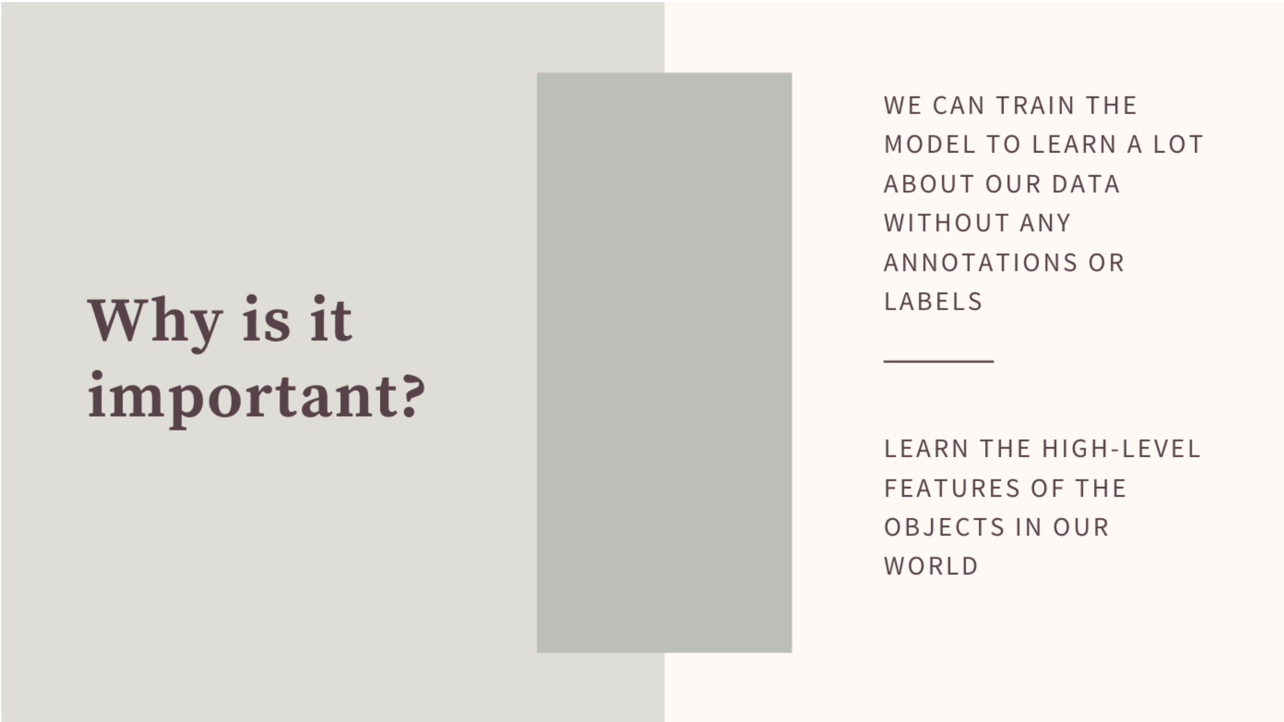
Slide 4:



Now why is this important? In most real-world scenarios, we don't have labels for each image. Take medical imaging, for instance. To create labels, professionals have to spend countless hours looking at images to manually classify, segment, etc. With contrastive learning, one can significantly improve model performance even when only a fraction of the dataset is labeled. Secondly, contrastive learning enables us to recognize the similarities and differences and learn high level features of the objects in our world. It just looks at pairs of data points and classifies them as similar or different in order to learn higher level features.

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Slide 5:

In order to effectively solve the proposed problem statement, an architecture of Contrastive Discriminator (ContraD) was suggested to be incorporated into the GAN discriminator. This suggested design will reduce the potential harm on the model performance which is caused due to existing data augmentation techniques. It will enable the GAN to learn a contrastive representation that is compatible to GAN. This means GAN would ultimately be able to distinguish between real and fake samples without breaking the contrastive learning. Hence, a small neural network discriminator is enough to perform its task upon the representation.

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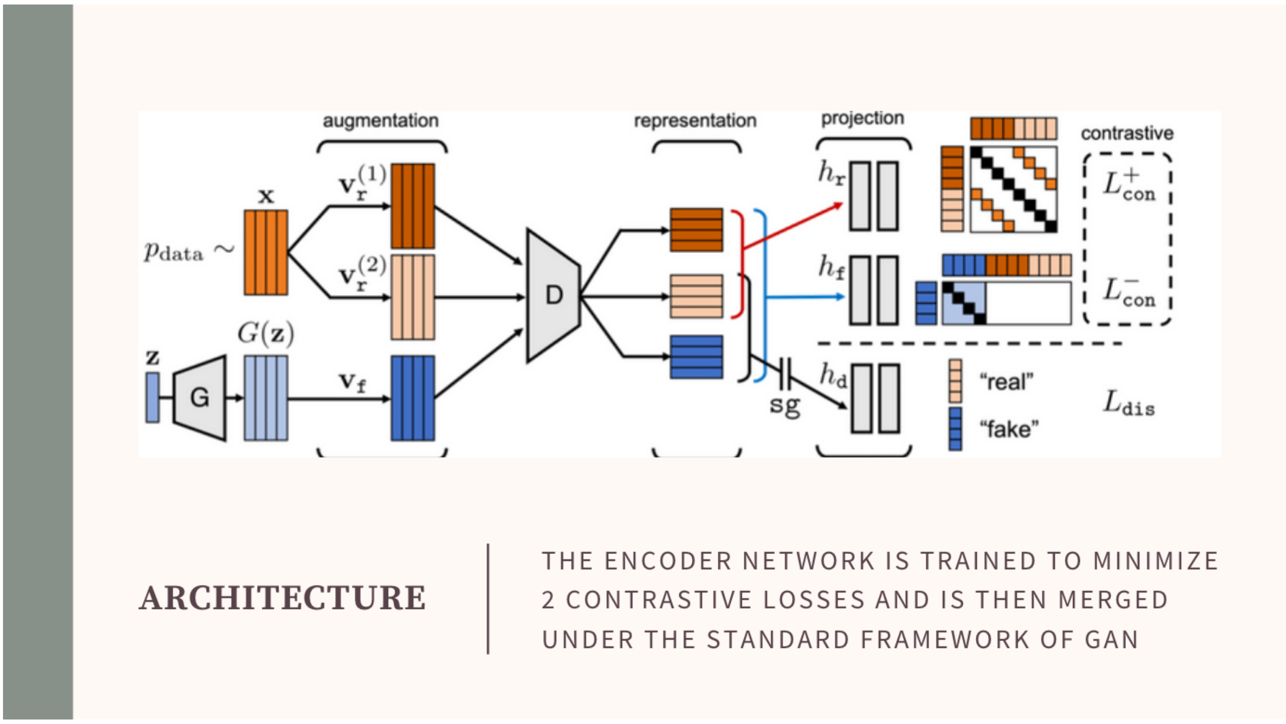
Slide 6:



Following image presents an overview of Contrastive Discriminator (ContraD). Overall, the representation of ContraD is not learned from the discriminator loss which is labelled as Ldis, but from two contrastive losses labelled Lcon+ and Lcon-, each representing the loss for real and fake samples respectively. It should be noted that sg(.) labelled in the image represents the stop-gradient operation which is an essential part of this design as it prevents performance degradation when a deeper discriminator such as SNResNet-18 is used. Now, I would like to pass it on to Harum for the remaining presentation.

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Slide 7:

Thank you Raahim.
Now, you must be wondering: how is this different from the previous methodologies beyond its distinct architecture? The answer to this is simple. This implementation enables the discriminators to work with a much stronger augmentations and simply does not increase the training instability and this results in the discriminator not being overfitted, which is a concern for many.

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Slide 8:

Moving onto the results, it was noted that GANs with ContraD consistently improved the FID and IS, which were the two primary measures of efficiency.
Additionally, it was also noted that the highly discriminative features were maintained in terms of linear evaluation.

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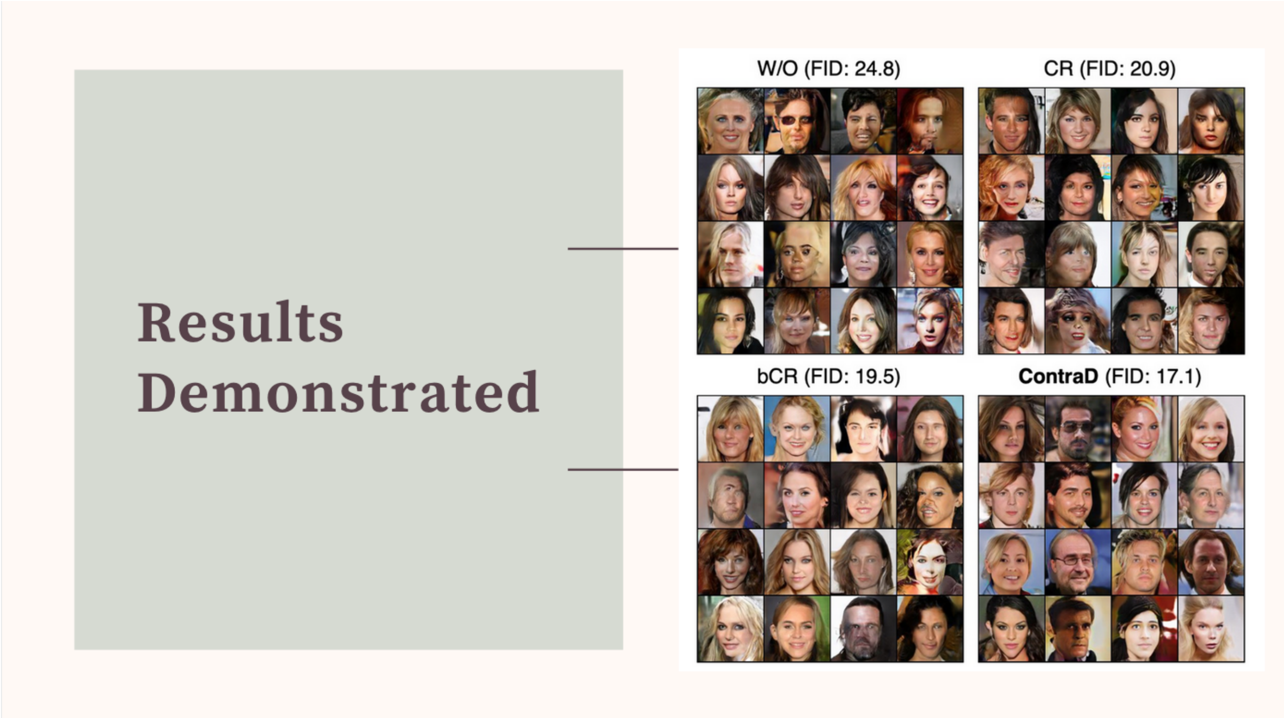
Slide 9:



Here is a visual representation of the results. You can see in the diagram that FID was the lowest for ContraD and it clearly outperformed all the other models, which means it is simply better than the other models when trained with GAN.

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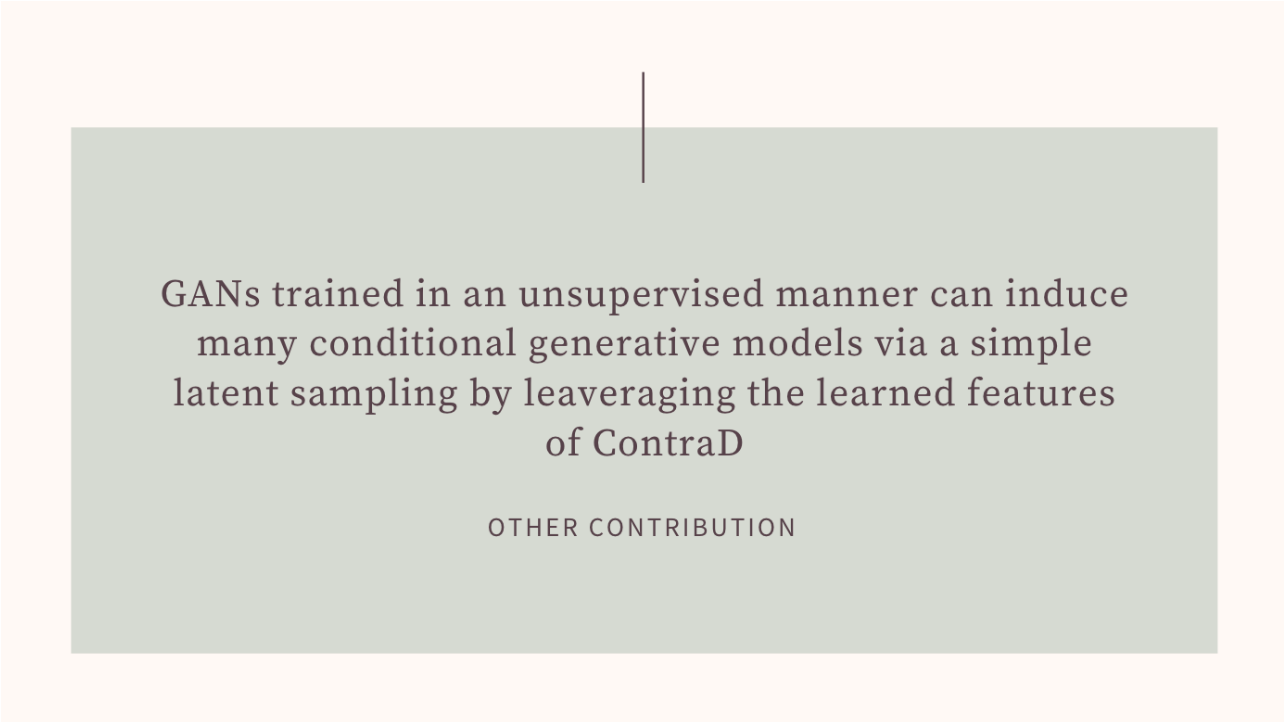
Slide 10:



Before we move onto the limitations and future work. We would like to point out an interesting observation that the authors made. They noticed that GANs which were trained without labels in an unsupervised manner induced many conditional generative models through simple latent sampling. This was done by leveraging the learned features of ContraD. I would also like to point out that it was noted that while the hyperparameters were kept constant, the only model which kept improving itself was ContraD.

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Slide 11:

Now onto the limitations.
Unfortunately, no limitations were mentioned in the paper by the authors and, despite trying to do so, we could not point out any either. This was primarily due to the lack of depth in the methodology steps.

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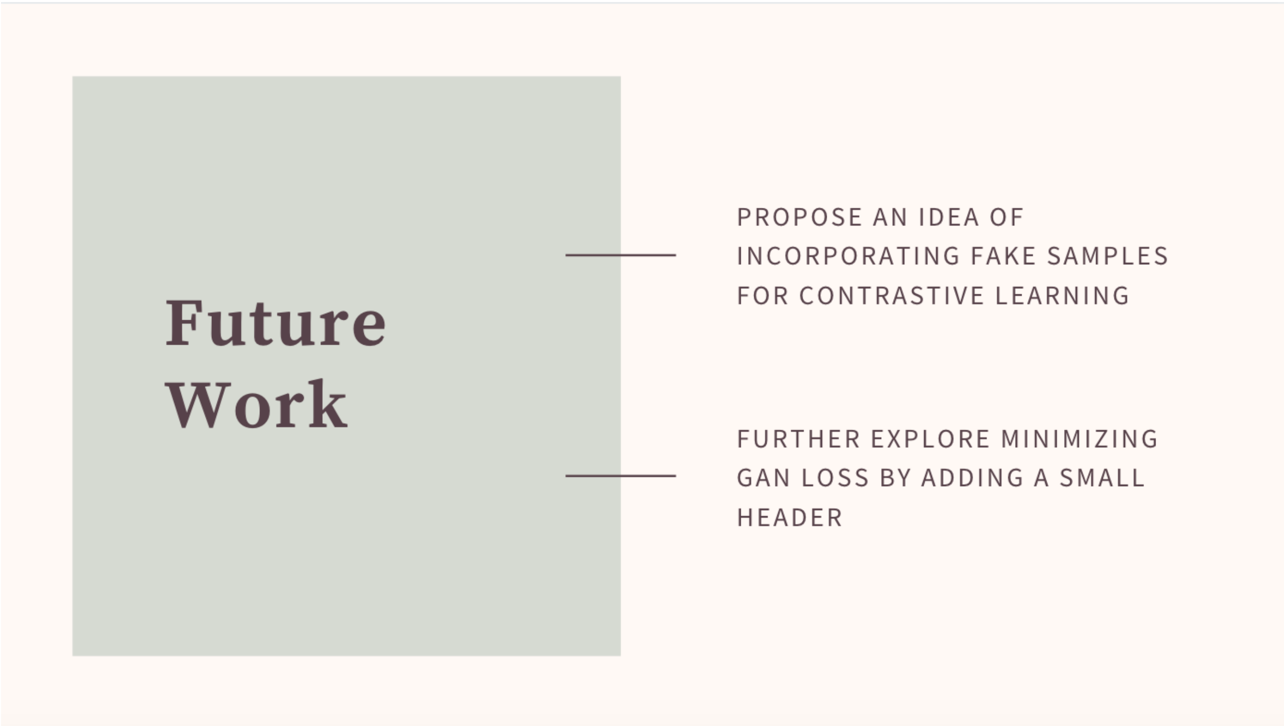
Slide 12:



For what work can be done in this area in the future, the authors showed an inclination towards further exploring minimizing GAN loss by adding a small header and additionally proposed an idea of incorporating fake samples for contrastive learning.

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Slide 13:

Thank you for listening to our presentation and that's it from our end.

Time - 5 seconds