Overview of GAN Applications

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Outline

- GAN applications
  - Image-to-image translation — and extensions to other modalities such as text, audio, and video
  - Image editing, art, and media
  - Medicine and climate change
- GAN adversarial concept use in other research areas

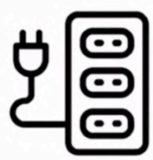
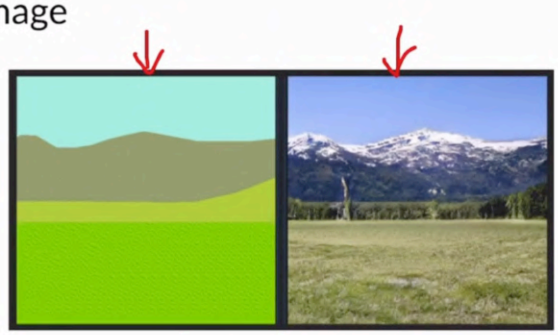


Image-to-Image



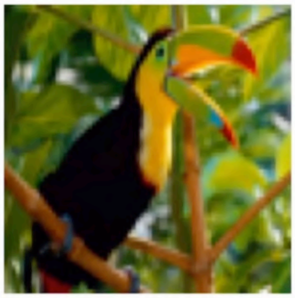
GauGAN

Available from: https://arxiv.org/abs/1903.07291

One cool application of GAN is being able to translate from one style to another. And here you can see you can sketch something on the left side very roughly and expect the GAN to generate a realistic photo of that for you. Where different colors in your schedule, represent different classes that you would like it to draw.

So here is showing a mountain that is in brown and grass in green, and this is using a GAN called GauGAN.

Image-to-Image

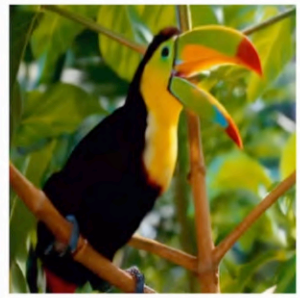


Original image

Super-Resolution GAN

Another application of image-to-image translation is Super-Resolution GAN.

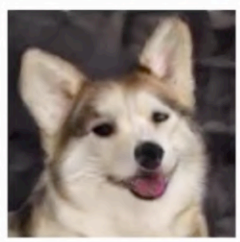
So taking an original image that is very low resolution and getting a much higher resolution image from that. This is really cool, because obviously you might have a lot of blurry images and you want to make them higher resolution. And using a GAN, it will look much more realistic than traditional up sampling techniques.



Sharpened image

Available from: https://arxiv.org/abs/1609.04802

Image-to-Image



Multimodal image-to-image translation

Available from: https://github.com/NVlabs/MUNIT

Image-to-image translation isn't just going from one domain to another domain, and there's a one-to-one mapping. In fact there is multimodal image-to-image translation as well. We're given this picture of a cat, you can map it onto a husky looking dog or a samoy at looking dog.

This is really cool because the model actually does not know what the classes of dogs are. You don't tell it you don't give it labels. So this is unsupervised and it figures out all the different dog breeds that this cat can map onto in your training data set.

Text-to-Image

Beyond image-to-image translation there's also text to image translation.

"The bird is black with green and has a very short beak."

We're given a sentence such as the bird is black with green and has a very short beak. Your GAN can take that and generate various images that match that sentence.

Available from: https://arxiv.org/abs/1612.03242

You also can map from multiple inputs to an output, meaning your conditioning on these inputs.

So here you're looking at an image of the Mona Lisa, and you're looking at various face landmarks. So actually you can take a video of someone talking and extract various face landmarks from their face. So where the eyes are, the eyebrows are, nose, mouth, etc and get a sense of that. And together as input into your model, you can get these various talking heads of the Mona Lisa that match these face landmarks and also the image of the Mona Lisa. So you can talk through the Mona Lisa.

Image-and-Landmark-to-Video

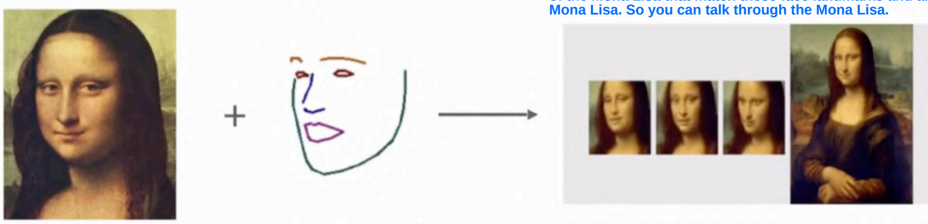
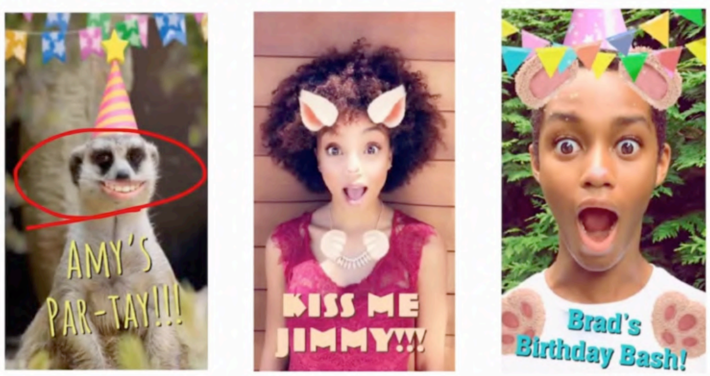


Image + Face landmark → Talking heads

Available from: https://arxiv.org/abs/1905.08233

Application Areas: Image Filters



Available from: https://www.snapchat.com

So GANs can also be used for image filters such as those on Snapchat. For example, here is a person being turned into maybe a lemur or something. And you can also use a GAN to add makeup for example, or change kind of what people look like.

Beauty companies are certainly looking into this, so you can try on makeup before actually buying it.

Application Areas: Image Editing

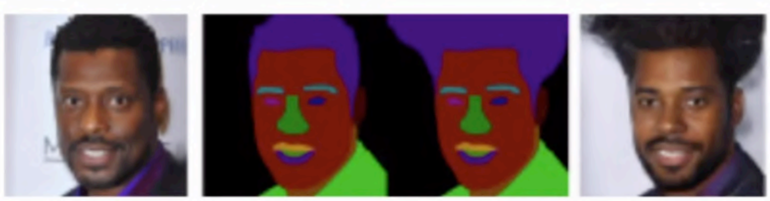


Image | Mask | Edited mask | Edited image

Image editing software

Available from: https://arxiv.org/abs/1907.11922

Another cool application area is image editing.

So say you have an image of a person here and you have a mask of that person. What you can do is actually you can edit that mask slightly, so you can change this mask a little bit right here with the hair I believe. And then you can get a different image, the GAN can take that edited mask and edit that image for you, such that you can have different hair now for this person.

Application Areas: Stylized Images

Democratized art

Available from: https://www.youtube.com/watch?v=85l961MmY8Y

As you can imagine GANs can be used to stylize various images. And this enables anyone who can build a GAN to produce beautiful artwork. And in a sense, this is democratizing art a little bit, making it easier for people to draw beautiful pieces of art where at least selecting from those GAN outputs what they want.

Application Areas: Data Augmentation

Real

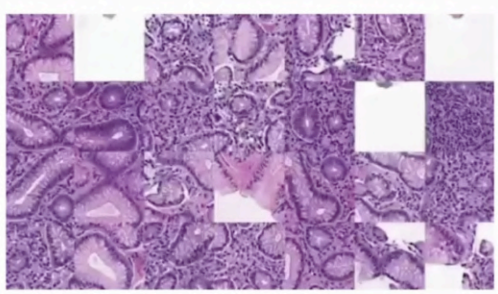
Increasing dataset size and diversity

Available from: https://arxiv.org/abs/1711.04340

GANs can also be used for data augmentation. Meaning the generated data can then be used to supplement real data for a downstream tasks such as classification or detection or segmentation, etc.

So we can increase your real data set size and diversity by using your generated samples.

Application Areas: Medicine



Simulating tissues

Available from: https://twitter.com/realSharonZhou/status/1182877446690852867

GANs have also been used in medical related areas. And this is an example of simulating tissues from a state of the art GAN. And these patches of tissues are typically seen by a medical pathologist.

A board certified pathologist actually cannot tell the difference between these simulated GAN generated tissues and real ones.

Application Areas: Climate Change

Real input

Generated output

Another cool application area is around climate change.

So in order for people to feel the visceral effects of climate change, perhaps we can grab any street view image such as this real input here. And be able to generate an output that looks like that place is flooded.

The goal of this work is to help people visualize what 1 degree maybe 2 degree of warming would do to the earth, to a place they might know. And this is published work I've done with Yoshua Bengio in his lab.

Available from: https://iopscience.iop.org/article/10.1088/2632-2153/ab7657/meta

Application Areas: Media

GANs can also be used in types of media. So on the right here is the generated sample of Amy Adams. And of course for this there are positive and negative implications. You might have heard about deepfakes, which generally has a negative connotation associated with it. Because it's often about stealing identities without permission.

But increasingly there have been more positive applications of GANs as well. We're simulating someone with a different identity might help protect them while lending them a voice.

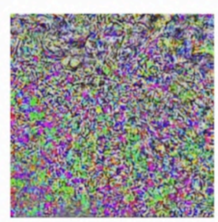
Deepfakes

Both pretty cute, actually

Available from: https://en.wikipedia.org/wiki/File:Deepfake_example.gif

Adversarial Research Areas

STOP!



Predicted class: airliner
Predicted probability: 96.8%

Adversarial examples & robustness

The adverse aerial concept behind GANs also seeps into other research areas.

For example, adversarial examples and robustness are pretty cool areas. And here's one instance where a pig image plus some adverse aerial noise actually gets a predicted class of an airliner. So the wrong predicted class with a probability of 96.8%. So we would definitely not want this to happen, and you can imagine instead of a pig maybe this is a stop sign. And that's even more dire because a self-driving car might not be able to see that.

So this is a huge area of research where people are looking at how to make our models more robust using various adverse aerial methods as well.

Finally, there are adjacent areas where GANs used as a subcomponent or a subnetwork. And their largely there because they can help improve the realism of the eventual output.

Available from: https://adversarial-ml-tutorial.org/introduction/

Summary

So in summary, image-to-image translation is a framework that generalizes too many different tasks, including those with text, audio, and different media in different modalities. There are many immediate application areas, including data augmentation. And additional fields that are adjacent to GANs use adverse aerial techniques for both improving realism by using GANs as a subcomponent, as well, as improving robustness of the model. Or ensuring that the model can still detect things even when there is some adverse aerial noise in the mix

- Image translation generalizes to many tasks
- Many immediate application areas, including data augmentation
- Other fields use adversarial techniques for realism and robustness

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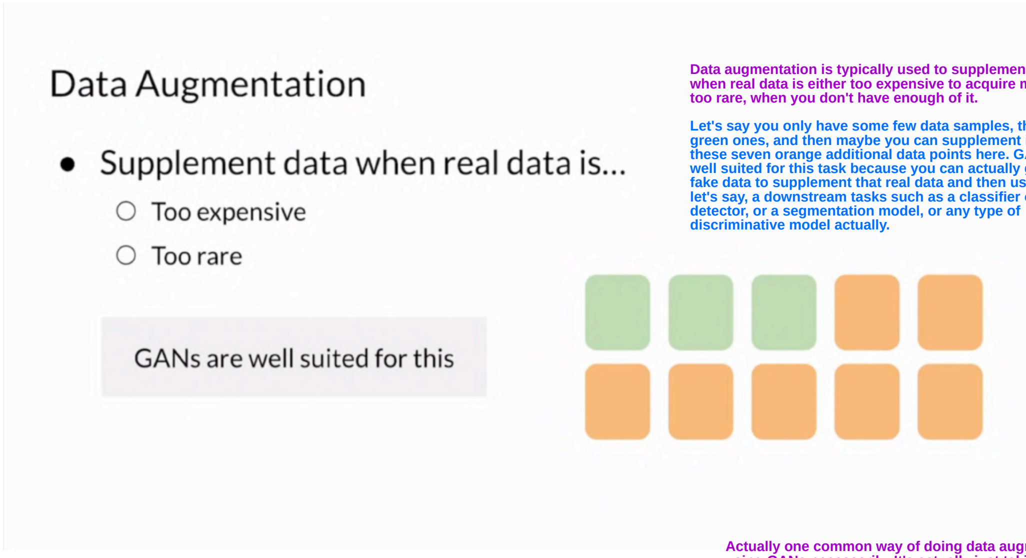
Data Augmentation: Methods and Uses

Outline

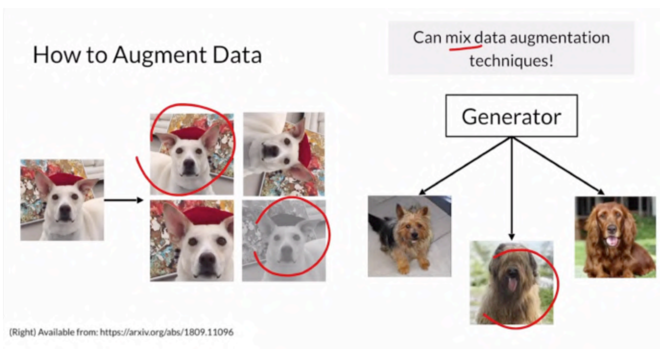
- Data augmentation
- Use cases for data augmentation
- Implementation of data augmentation

First you'll learn about what data augmentation is, what it's used for, and then how to implement it in the context of GANs.



Data augmentation is typically used to supplement data when real data is either too expensive to acquire more of or too rare, when you don't have enough of it.

Let's say you only have some few data samples, these green ones, and then maybe you can supplement it with these seven orange additional data points here. GANs are well suited for this task because you can actually generate fake data to supplement that real data and then use that for, let's say, a downstream tasks such as a classifier or a detector, or a segmentation model, or any type of discriminative model actually.



Actually one common way of doing data augmentation is not using GANs necessarily. It's actually just taking an input image. Let's say you have this one image in your real dataset. Your task right now is to detect whether there is a dog and the image using a classifier. You're turning your classifier with this image, but maybe your classifier doesn't have enough data. What you can do with this image is, you can do all sorts of augmentations on this image and then feed all of these images in to the classifier as real data as well.

Now how a GAN could help with data augmentation, is that it can generate a ton of different images. Here you can see that it's generating all sorts of different dogs, and its diversity far exceeds what is seen here, at least in the breed of dog, and even in the lighting schemes and everything in the background, even in the orientation in some ways as well. Of course it's not as rotated as that dogs, so perhaps these methods could be overlaid with each other. You can in fact use all of these methods, traditional data augmentation techniques such as crop, flip, rotate, and using again to augment your data as well. Definitely you can mix all of these data augmentation techniques.

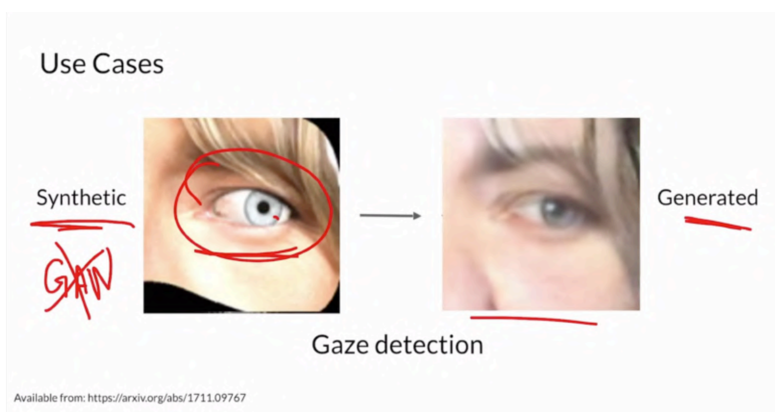
A fun fact is that there is a cool body of literature that explores how to best combine images from all different types of data augmentation techniques. That body of literature, tries to find some kind of policy in determining which image you need to give at what point to your classifier. If you're interested in that, I would start exploring something called RandAugment.

How can this be useful, specifically the GAN generated data, how can this be useful in data augmentation?

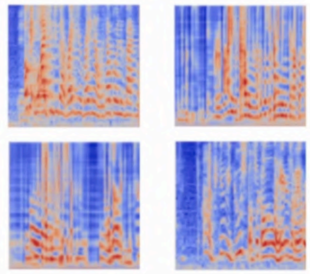
Well, one interesting use case, is that in social sciences, people often use gaze detection to determine where someone is looking and focusing in their studies. It's really hard to collect additional samples on which direction an eye might be looking. Typically what these researchers do is they generate synthetic examples that are not necessarily generated by a GAN. These are synthetic, but this is a fake eye generated with a graphics computer program. Unfortunately, this actually doesn't help the downstream classifier. There's something odd about the synthetic example that is not useful. The realism that the GAN generated data gives is much better and improves the downstream classifiers significantly.

That's actually quite an interesting task where now we can use GAN generated data in addition to real data to then help with classifying which way an eye is looking. This is for a social science application.

I'd like to emphasize here that this data is hard to collect. That's why we need to maybe generate or augment this dataset a little bit more. That's hard to collect because it's hard to call in new participants and ask them if it's okay to take a video of their eyes, and to get thousands of participants, that would be very costly.



Use Cases



Speech emotion recognition

Available from: https://pdfs.semanticscholar.org/395b/ea6f025e599db710893acb6321e2a1898a1f.pdf

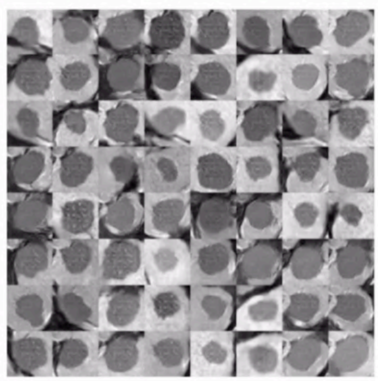
Another interesting use case is in speech emotion recognition. What that means is when you're speaking, detecting what emotion you might have in your speech is an interesting task where there isn't that much data out there that's labeled on whether someone sound angry or happy.

This could be important for, let's say, your Alexa and Google Home or something that is trying to detect what your emotion is, to try to help you, hopefully in a very positive way. There are perhaps some real samples of angry sounding voices and happy sounding voices, and these look really interesting. They lack a visual. These are spectrograms, which is a visual representation of the spectrum of frequencies that a person might give out when they do speak.

Based on some literature, these spectrograms have notable signatures that are associated with being angry or happy or other emotions. While it might be difficult to gather more data, you could perhaps instead use a GAN to generate some fake spectrograms for you as well.

Use Cases

Synthetic liver lesions



Available from: https://arxiv.org/abs/1803.01229

The data you're working with might also be very hard to obtain, such as brain scans or mammograms of tumors due to patient privacy. You can use a GAN to actually generate synthetic liver lesions. These are liver lesions generated by DCGAN.

In other cases, it might be unethical to acquire more data samples. Like if you're trying to get cancer samples, you don't want to cause cancer in people. You don't want to get data that you're not supposed to be accessing from another institution, for example, so generating fake data could be one option there.

Summary

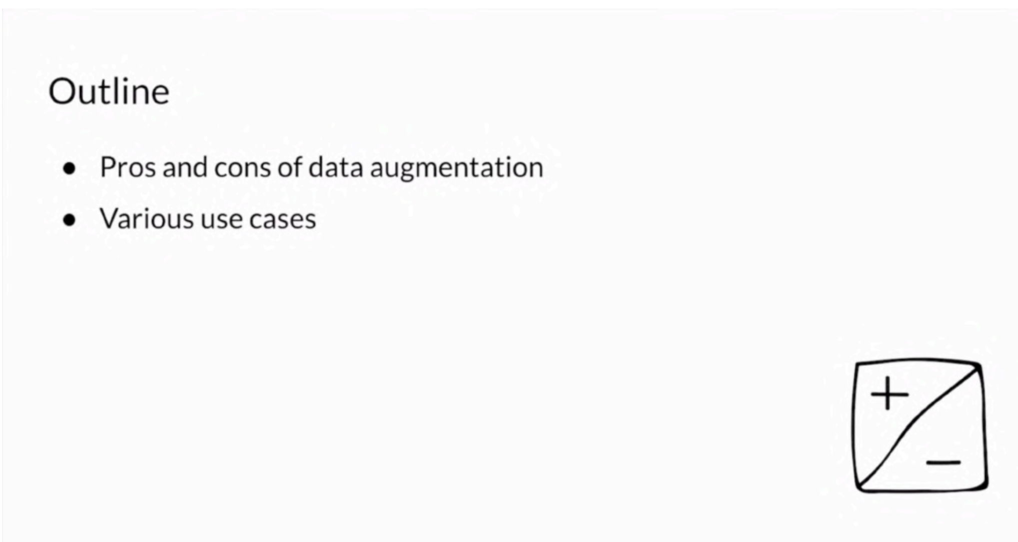
- Use GANs to generate fake data when real data is too scarce
- GANs have various use cases in data augmentation and beyond!

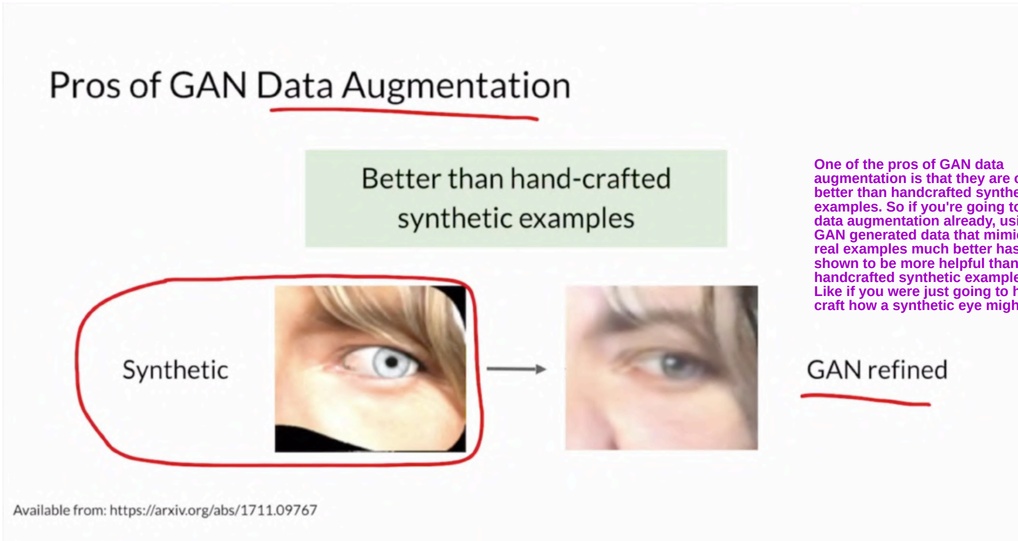
In summary, GANs are useful in generating fake data when real data is either too hard to come by or expensive to acquire. GAN generated data has very cool immediate use cases, including the data augmentation use case, you see here.

(Optional) Automated Data Augmentation

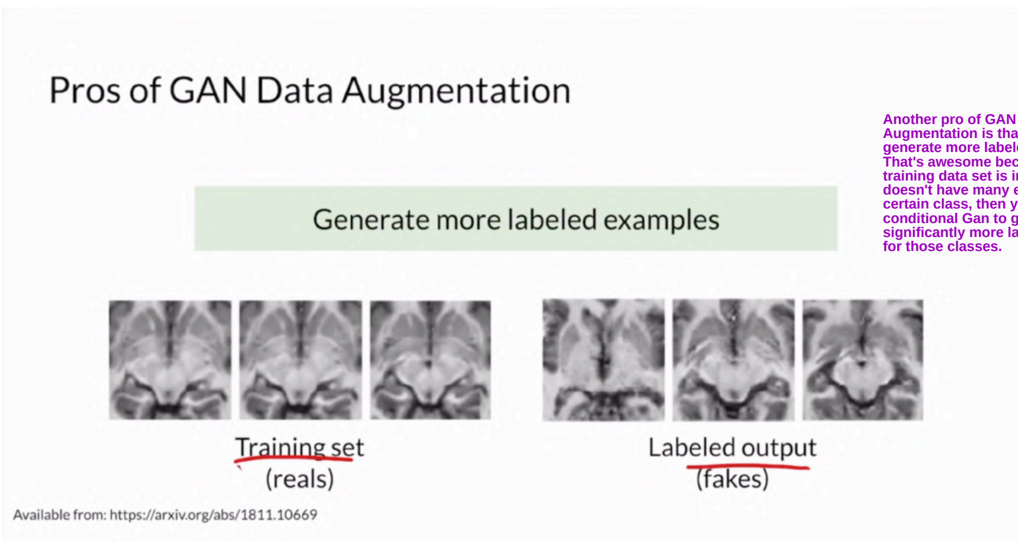
Interested in mixing data augmentation techniques and automated augmentation policies? Take a look at the paper mentioned in the previous video!

RandAugment: Practical automated data augmentation with a reduced search space (Cubuk, Zoph, Shlens, and Le, 2019): https://arxiv.org/abs/1909.13719

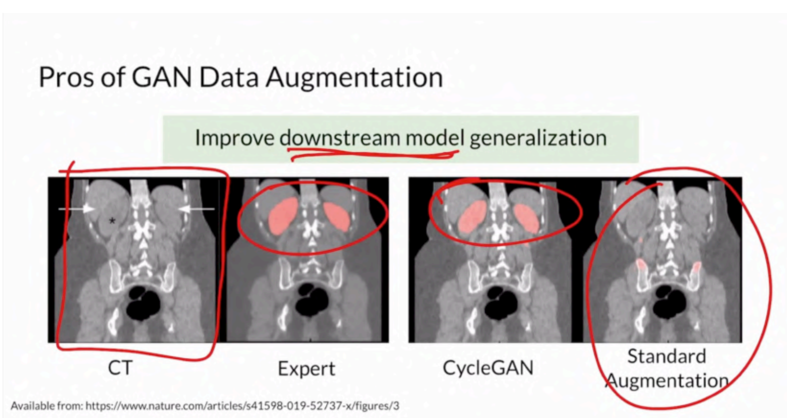




One of the pros of GAN data augmentation is that they are often better than handcrafted synthetic examples. So if you're going to use data augmentation already, using GAN generated data that mimics the real examples much better has shown to be more helpful than handcrafted synthetic examples. Like if you were just going to hand craft how a synthetic eye might look.



Another pro of GAN Data Augmentation is that you can generate more labeled examples. That's awesome because if your training data set is imbalanced or doesn't have many examples of a certain class, then you can use your conditional Gan to generate significantly more labeled examples for those classes.



Finally one other pro of GAN data augmentation, is that it can improve your downstream models generalization.

So in this example, the downstream model and the downstream task is to segment a CT scan and so here you can see an expert segmenting it here, so this would be the ground truth. But say you don't have that much time or money to pay experts who are doctors with limited time an anytime you take away from them is probably time taken away from saving a life. So your setup is maybe you have a few expert examples and then you can get your GAN to generate more data that mimics what expert is doing for your downstream model to learn better segmentation.

And here is also an example of how standard augmentation, which you saw previously using manually generated synthetic examples doesn't work as well. It's further away from how the expert is segmenting there.

Cons of GAN Data Augmentation

Diversity is limited to the data available

Training set

Generated outputs

So, candid augmentation is obviously not perfect, it won't be able to cover the entire diversity of what you need if you're training data set is limited as well. The diversity of your generated outputs will still rely heavily on the diversity of your training data set.

Cons of GAN Data Augmentation

Not useful when overfit to real data

Real

Fake

Available from: https://arxiv.org/abs/1902.04202

Related to that issue, if your GAN starts in memorize or mimic the real data so much that the fakes almost look identical to the real. Basically over fit to the real data in some way, then it might not be helpful to supplement your task with this fake data. If it already looks like the real data, it won't help your downstream task at all, it's just like training another epoch on your real data.

Summary

- Pros:
  - Can be better than hand-crafted synthetic examples
  - Can generate more labeled examples
  - Can improve a downstream model's generalization
- Cons:
  - Can be limited by the available data in diversity
  - Can overfit to the real training data

In summary, the pros of GAN data augmentation is that it can be better than handcrafting synthetic examples for data augmentation, it can generate more labeled examples, especially if you're using your conditional GAN. And it has been shown to improve downstream model generalization across a variety of tasks, including image segmentation, classification and detection.

There are certainly cons for using GAN generated data, or data augmentation an the first is that its diversity will be limited to whatever your training data set has. So you want to augment a real class with GAN generated data, but if you really just don't have that many samples for your GAN to learn from, it will still be limited by that diversity. Additionally, if your GAN does happen to start mimicking in your entire real training data set, that will be unhelpful as well in terms of data augmentation, because that would just be the same as training and additional epoch on your real data set.

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GANs for Privacy

Outline

- GANs for privacy preservation
- Medical privacy as a motivating example

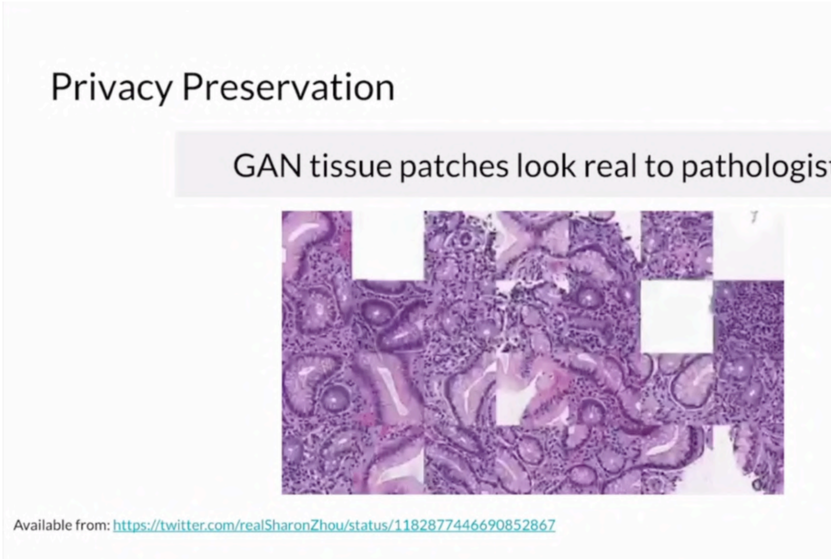
Motivations for Medical Privacy

- Protects real patient data
- Can encourage data-sharing between institutions
- Less expensive and more abundant than real data

So Medical Privacy is important because you want to protect real patient data. Often using real patient data in your models can harm the patients if someone reverse engineers your model and figures out who those people are or if that data is somehow released.

Ensuring that medical data is private can encourage data-sharing between different institutions because that would not breach any personal health information or PHI issues.

Finally, if you had simulated medical data from again, for example, that is certainly less expensive to acquire and certainly more abundant because you can keep generating infinitely then real data.



So one really impressive thing is that GANs can generate data that look real to the human eye and specifically to a trained medical doctor as I as well. And so these samples of tissues look realistic to pathologists who look at these every day.

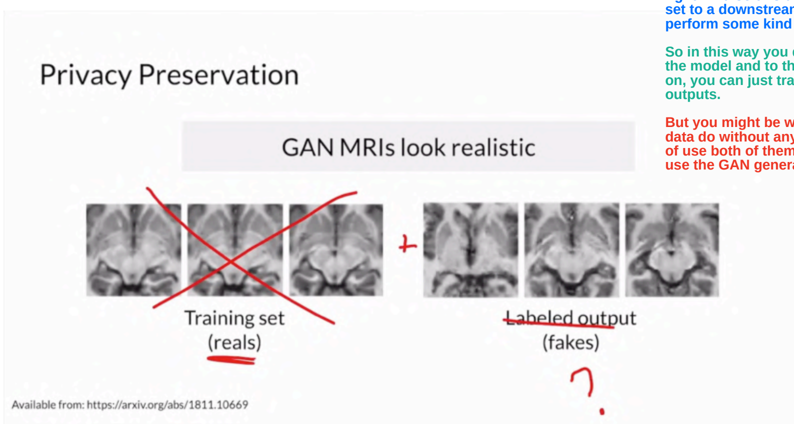
But I would say in this particular example, even though it's medical data Privacy isn't exactly being breached, because these are examples of intestinal tissue without very clear personal markers being shown.

But I would say that MRIs scans or CT scans or X-rays sometimes have markers that can give away who a person is on the scan.

Here is an example of a GAN mimicking MRI scans, here on the right. And so this data can be used in lieu of your real training data set to a downstream model that I may want to use MRI data to perform some kind of classification or segmentation.

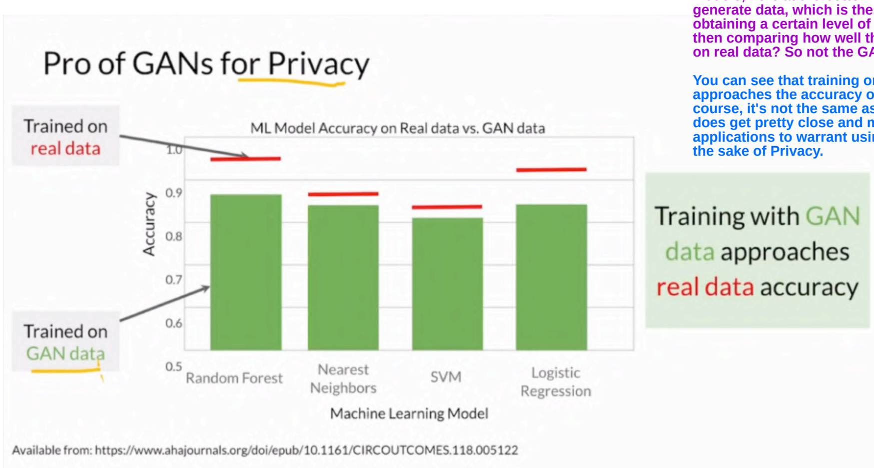
So in this way you don't have to expose the real training data set to the model and to then whoever is going to be using that model later on, you can just train the model using these GAN generated outputs.

But you might be wondering how well does this GAN generated data do without any of the reals? So in data augmentation you kind of use both of them, but in Privacy Preservation you only want to use the GAN generated data. But how well does it do exactly?



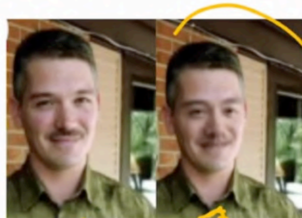
So here's a graph showing various Machine Learning Models, here at the bottom. Trained on either just GAN generate data, which is these green bars here and obtaining a certain level of accuracy on each one. And then comparing how well that model does on just training on real data? So not the GAN generated data

You can see that training on just GAN generated data approaches the accuracy of training on real data. Of course, it's not the same as training on real data, but it does get pretty close and might be enough for some applications to warrant using this GAN generated data for the sake of Privacy.



Con of GANs for Privacy

GAN sample is nearly identical to a real sample



Available from: https://arxiv.org/abs/1902.04202

Now before you jump in and use GANs for every Privacy application out there, note that there are caveats to using this approach. So it is very possible that your GAN will generate samples that look nearly identical to your reals. And that's really bad because you are no longer preserving the Privacy of, say his person, where the right is this generated sample and the left is the real.

So there are some ways to post-process this data to ensure that any samples that look sufficiently close to the reals will be removed in some way or not used in some way. But that could be pretty tough, I think the best bet you have here is to know that while the GAN can very likely generate a lot of the samples in your real data set. It will also generate a ton of other different types of samples such that probabilistically no one will know which ones are real and which ones are fake.

Summary

- GANs can be useful for preserving privacy
  - Sensitive medical data serves as one example
- Caveat: generated samples may mimic the reals too closely
  - Post-processing may help avoid this data leakage

In summary, GANs can be used for preserving privacy with sensitive medical data as one example. And the Caveat with using GANs for preserving privacy is that the generated samples might look exactly like the real ones or very close to the real one such that it doesn't feel like you're preserving privacy anymore. But because when you're sampling from a GAN you don't know which ones mimic the reals or fakes as someone using that GAN it can still be used for various applications for preserving privacy and not breaching it because you don't know which samples are actually the ones mimicking the reals. Of course, if you have a GAN that completely just memorizes data and doesn't really learn much else, then you have many issues there.

Of course some post-processing might help with this data leakage, such as finding the samples that are too close to the reals and throwing them out. But of course a post-processing sub might not be perfect.

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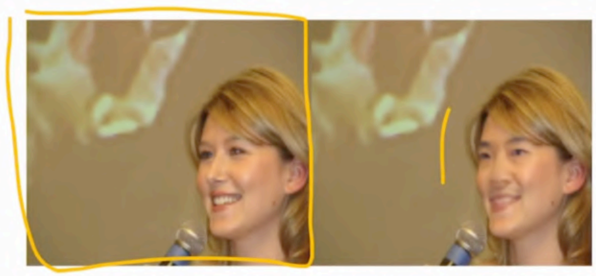
GANs for Anonymity

Outline

- GANs for anonymity
  - Concealing identity
  - Stealing identity
  - DeepFakes

Anonymity

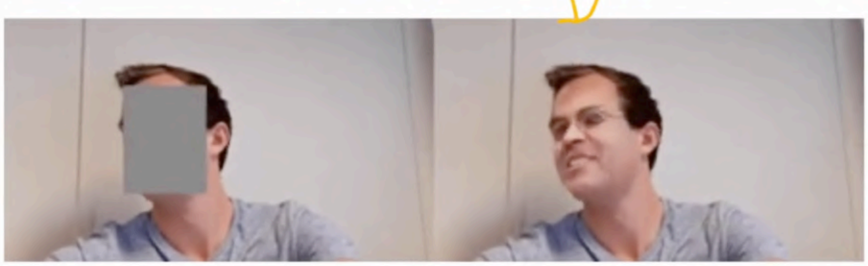


Original image   De-identified image

Available from: https://arxiv.org/abs/1902.04202

Take this original image of a woman, a GAN can actually generate a different face for her. So if you look closely, that is a different face, and this would be one way to preserve the anonymity of this person.

Anonymity



Available from: https://arxiv.org/abs/1909.04538

Here's an example of blocking out a man's face. The GAN can still generate a very realistic person across various frames. Of course, you see kind of glasses coming in and out because there isn't as much temporal continuity across the frames.

Pro of GANs for Anonymity

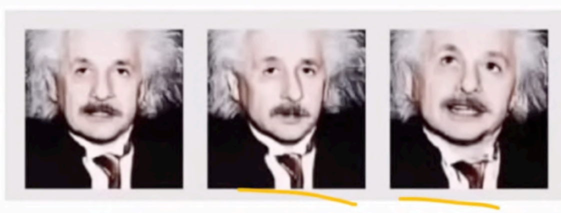
- Provide safe environment for expression to:
  - Stigmatized groups
  - Assault victims
  - Witnesses
  - Activists

Before diving into the risks of this because this is certainly a risky thing to do, concealing identity can be really important for safe expression among various groups.

For example, stigmatized groups like sexual assault victims, various witnesses, or various activists who might need to conceal their identity to stay safe. And yet they still want to have a way to be able to express themselves, and they can do that through a different face, for example. In their documentaries now enabling certain groups who would otherwise be uncomfortable being on camera, use a different face to still express themselves and speak out about their issues.

Con of GANs for Anonymity

Deepfakes put words into people's mouths



Available from: https://arxiv.org/abs/1905.08233

The downside of using GANs for anonymity is identity theft. For example, you might have heard of Deepfakes, which can certainly put words in people's mouths. So this is Einstein and someone else can talk through Einstein, and that's obviously not good. And you can imagine a lot of different people who would not want to say certain things, and other people can now say things for them, so this is not a good application.

Summary

- GANs can enable healthy anonymous expression for stigmatized groups
- GANs for anonymization can be used for good or evil
  - Identity theft is not good
  - Use your powers for good

So in summary, GANs do have the power to enable healthy expression for various stigmatized groups and help them remain anonymous while still expressing themselves through a realistic looking face.

However, I would say that GANs anonymization can be used for both good and evil. Identity theft is certainly not good with Deepfakes.

(Optional) Talking Heads

Fascinated by how you can use GANs to create talking heads and deepfakes? Take a look at the paper!

Few-Shot Adversarial Learning of Realistic Neural Talking Head Models (Zakharov, Shysheya, Burkov, and Lempitsky, 2019): https://arxiv.org/abs/1905.08233

(Optional) De-identification

Curious to learn more about how you can de-identify (anonymize) a face while preserving essential facial attributes in order to conceal an identity? Check out this paper!

De-identification without losing faces (Li and Lyu, 2019): https://arxiv.org/abs/1902.04202

(Optional) GAN Fingerprints

Concerned about distinguishing between real images and fake GAN generated images? See how GANs leave fingerprints!

Attributing Fake Images to GANs: Learning and Analyzing GAN Fingerprints (Yu, Davis, and Fritz, 2019): https://arxiv.org/abs/1811.08180

Works Cited

All of the resources cited in Course 3 Week 1, in one place. You are encouraged to explore these papers/sites if they interest you! There are many resources this week and much of it is recent research on emerging uses of GANs. They are listed in the order they appear in the lessons.

From the videos:

- Semantic Image Synthesis with Spatially-Adaptive Normalization (Park, Liu, Wang, and Zhu, 2019): https://arxiv.org/abs/1903.07291
- Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network (Ledig et al., 2017): https://arxiv.org/abs/1609.04802
- Multimodal Unsupervised Image-to-Image Translation (Huang et al., 2018): https://github.com/NVlabs/MUNIT
- StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks (Zhang et al., 2017): https://arxiv.org/abs/1612.03242
- Few-Shot Adversarial Learning of Realistic Neural Talking Head Models (Zakharov, Shysheya, Burkov, and Lempitsky, 2019): https://arxiv.org/abs/1905.08233
- Snapchat: https://www.snapchat.com
- MaskGAN: Towards Diverse and Interactive Facial Image Manipulation (Lee, Liu, Wu, and Luo, 2020): https://arxiv.org/abs/1907.11922
- When AI generated paintings dance to music... (2019): https://www.youtube.com/watch?v=85l961MmY8Y
- Data Augmentation Generative Adversarial Networks (Antoniou, Storkey, and Edwards, 2018): https://arxiv.org/abs/1711.04340
- Training progression of StyleGAN on H&E tissue fragments (Zhou, 2019): https://twitter.com/realSharonZhou/status/1182877446690852867
- Establishing an evaluation metric to quantify climate change image realism (Sharon Zhou, Luccioni, Cosne, Bernstein, and Bengio, 2020): https://iopscience.iop.org/article/10.1088/2632-2153/ab7657/meta
- Deepfake example (2019): https://en.wikipedia.org/wiki/File:Deepfake_example.gif
- Introduction to adversarial robustness (Kolter and Madry): https://adversarial-ml-tutorial.org/introduction/
- Large Scale GAN Training for High Fidelity Natural Image Synthesis (Brock, Donahue, and Simonyan, 2019): https://openreview.net/pdf?id=B1xsqj09Fm
- GazeGAN - Unpaired Adversarial Image Generation for Gaze Estimation (Sela, Xu, He, Navalpakkam, and Lagun, 2017): https://arxiv.org/abs/1711.09767
- Data Augmentation using GANs for Speech Emotion Recognition (Chatziagapi et al., 2019): https://pdfs.semanticscholar.org/395b/ea6f025e599db710893acb6321e2a1898a1f.pdf
- GAN-based Synthetic Medical Image Augmentation for increased CNN Performance in Liver Lesion Classification (Frid-Adar et al., 2018): https://arxiv.org/abs/1803.01229

- GANsfer Learning: Combining labelled and unlabelled data for GAN based data augmentation (Bowles, Gunn, Hammers, and Rueckert, 2018): https://arxiv.org/abs/1811.10669
- Data augmentation using generative adversarial networks (CycleGAN) to improve generalizability in CT segmentation tasks (Sandfort, Yan, Pickhardt, and Summers, 2019): https://www.nature.com/articles/s41598-019-52737-x/figures/3
- De-identification without losing faces (Li and Lyu, 2019): https://arxiv.org/abs/1902.04202
- Privacy-Preserving Generative Deep Neural Networks Support Clinical Data Sharing (Beaulieu-Jones et al., 2019): https://www.ahajournals.org/doi/epub/10.1161/CIRCOUTCOMES.118.005122
- DeepPrivacy: A Generative Adversarial Network for Face Anonymization (Hukkelås, Mester, and Lindseth, 2019): https://arxiv.org/abs/1909.04538

From the notebook:

- GAIN: Missing Data Imputation using Generative Adversarial Nets (Yoon, Jordon, and van der Schaar, 2018): https://arxiv.org/abs/1806.02920
- Conditional Infilling GANs for Data Augmentation in Mammogram Classification (E. Wu, K. Wu, Cox, and Lotter, 2018): https://link.springer.com/chapter/10.1007/978-3-030-00946-5_11
- The Effectiveness of Data Augmentation in Image Classification using Deep Learning (Perez and Wang, 2017): https://arxiv.org/abs/1712.04621
- CIFAR-10 and CIFAR-100 Dataset; Learning Multiple Layers of Features from Tiny Images (Krizhevsky, 2009): https://www.cs.toronto.edu/~kriz/learning-features-2009-TR.pdf