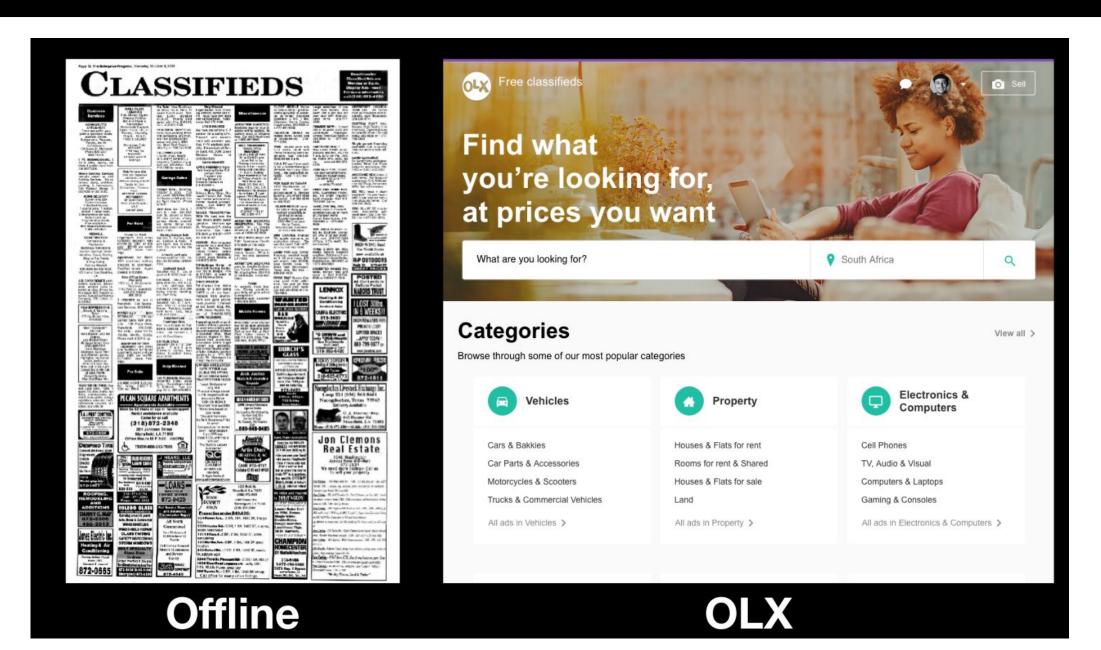


Semi-supervised learning with GANs: putting together the pieces together

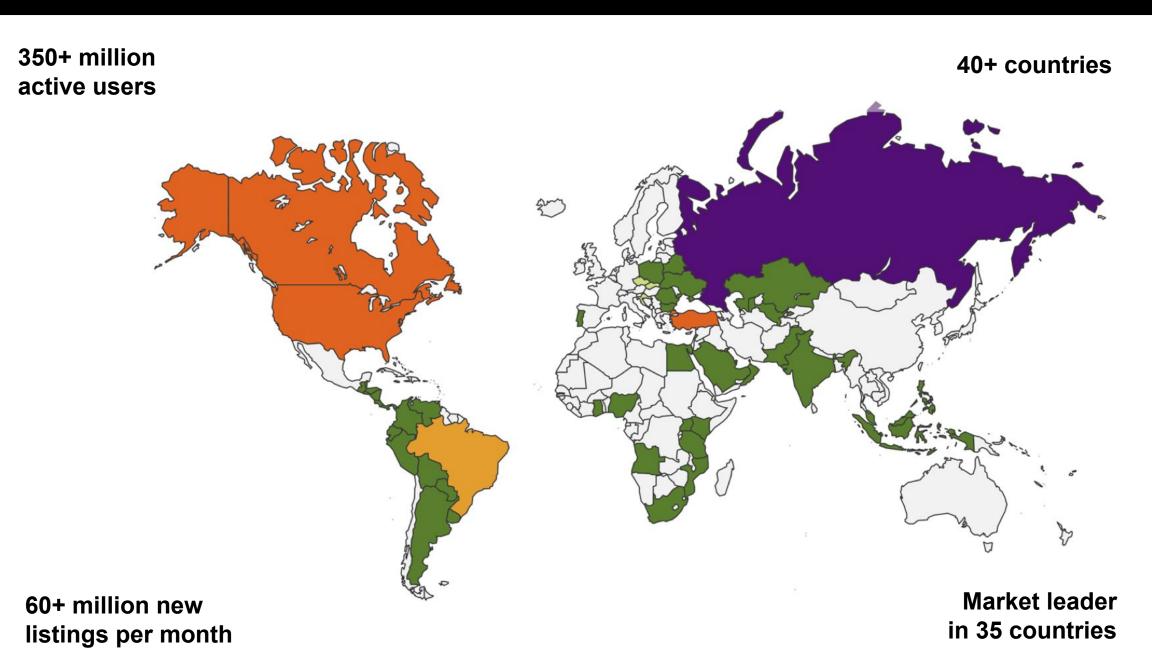
OLX Berlin Data Science Team

Classifieds



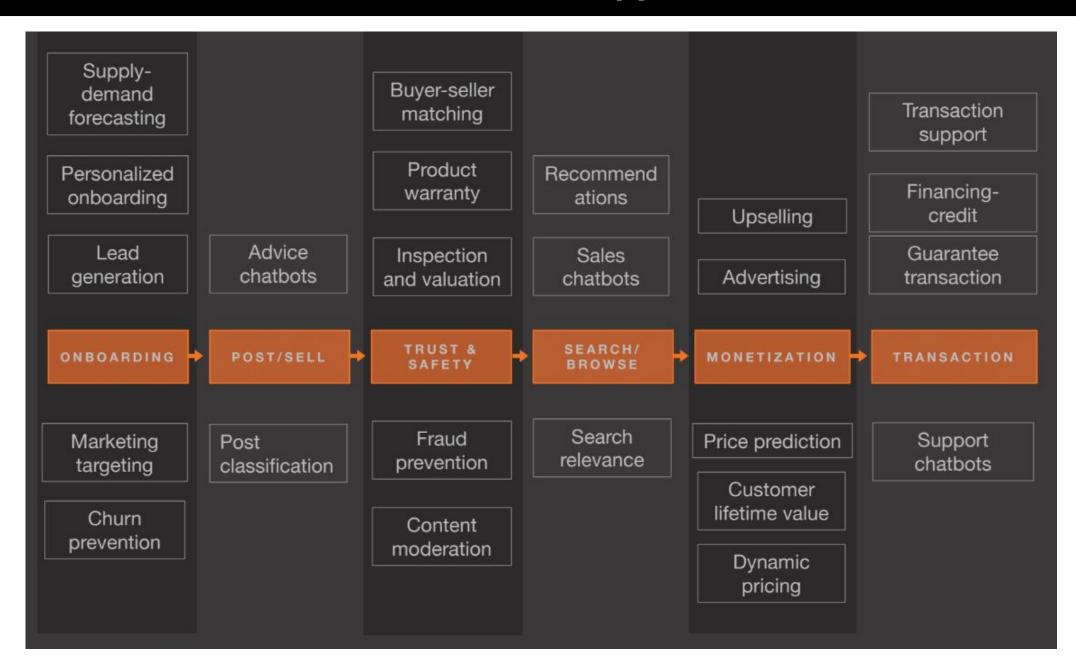


OLX in a glance





Classifieds - Data Science areas of Application





Outline

Short Intro

What are GANs

How GANs help in a semi-supervised setup

Using Colaboratory to train a GAN for semi-supervised learning

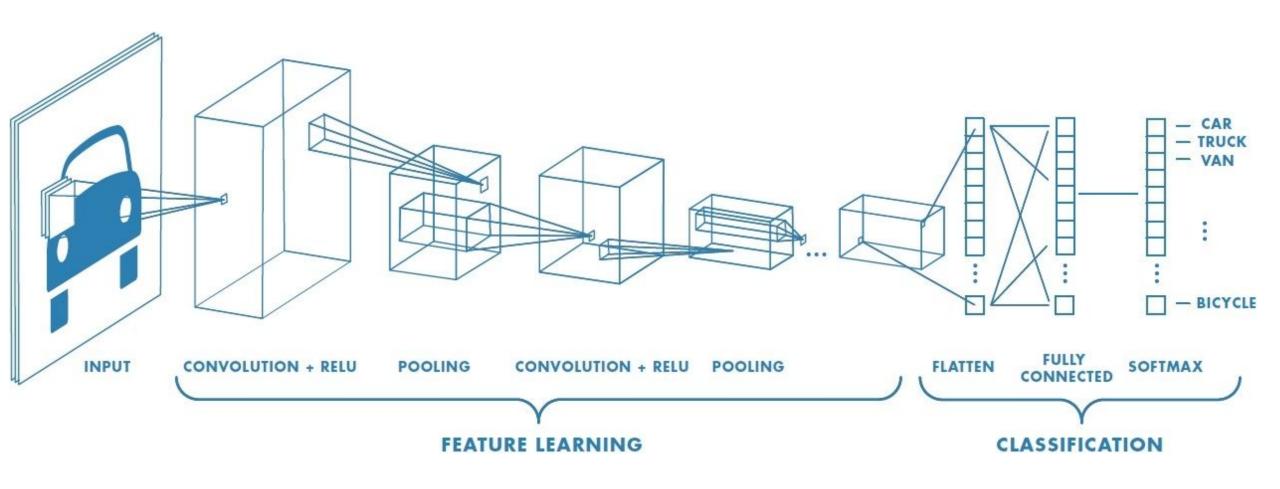
Options for putting the model in production



Intro to Deep Learning

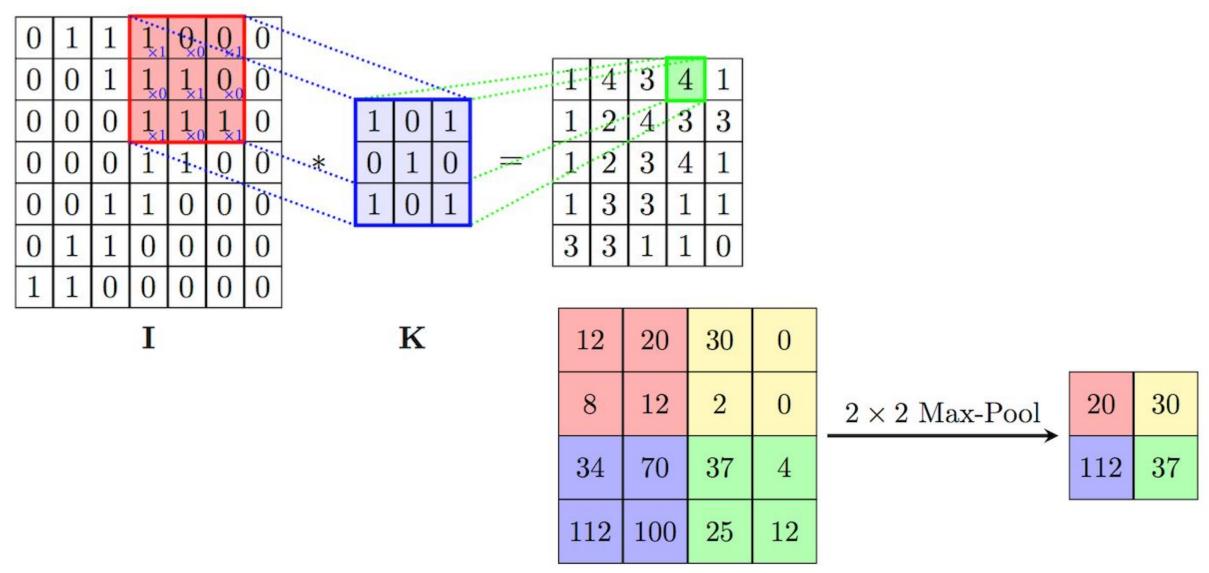


Convolution Neural Networks in two images - part 1



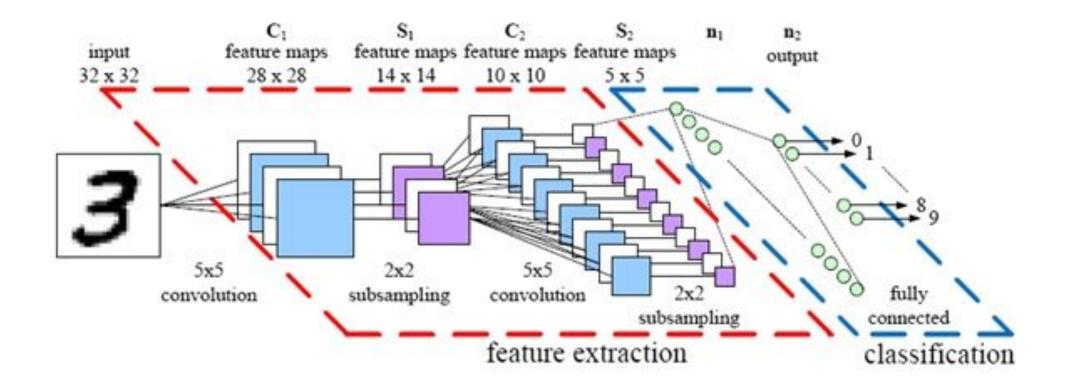


Convolution and Pooling





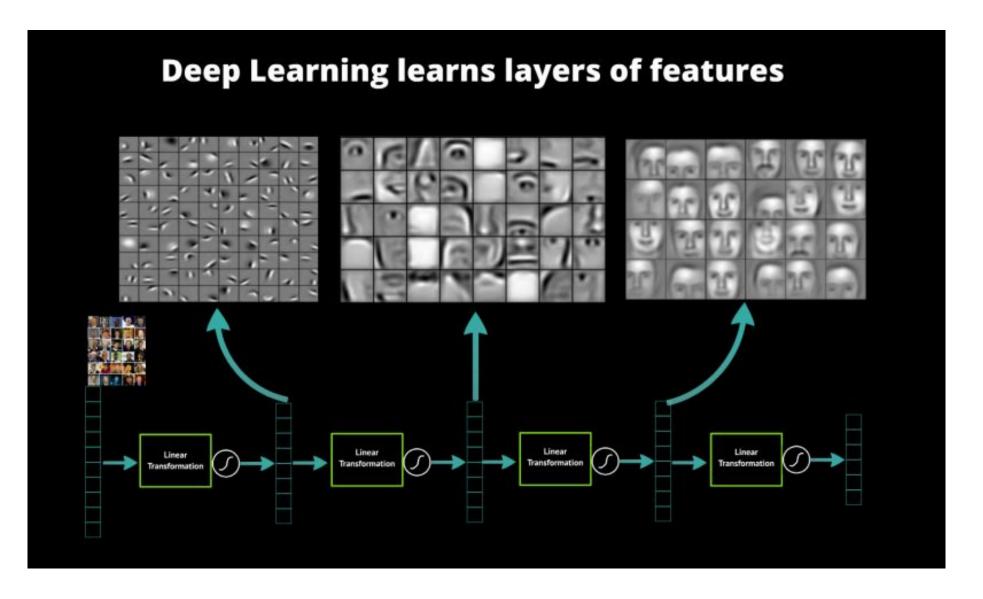
Convolution Neural Networks in two images - part 2





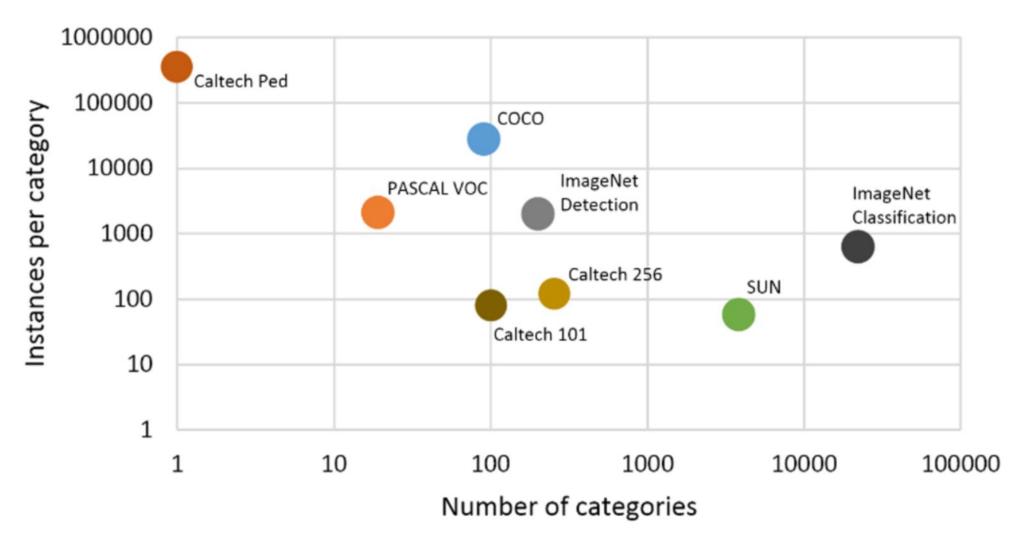
Why does it work so well?







Number of categories vs. number of instances



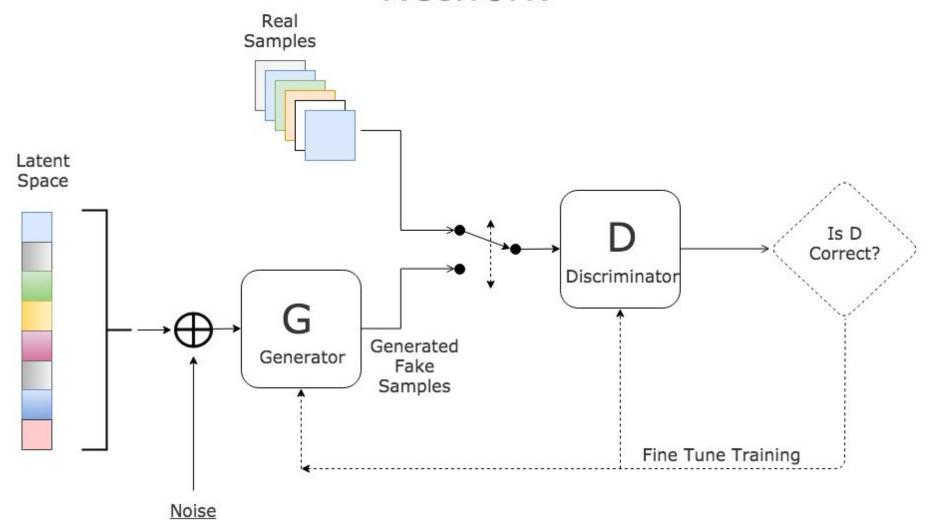


Source: https://arxiv.org/pdf/1602.07332.pdf

Generative Adversarial Networks

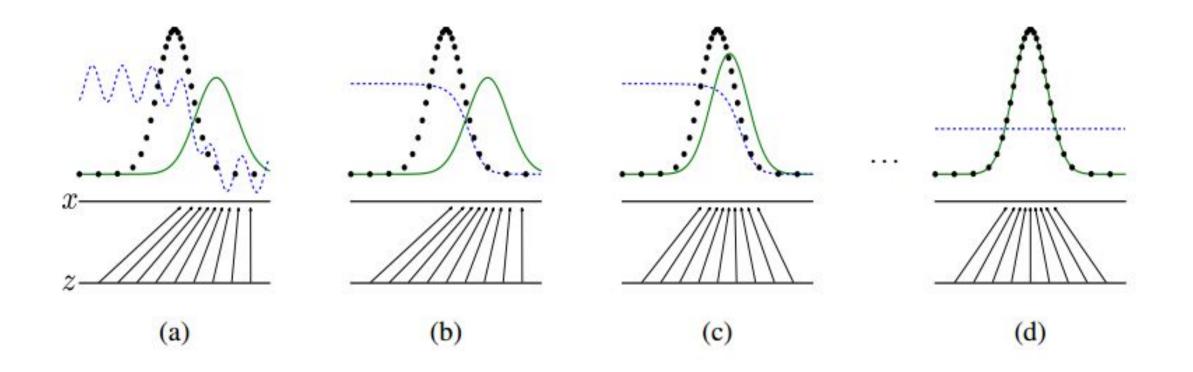


Generative Adversarial Network



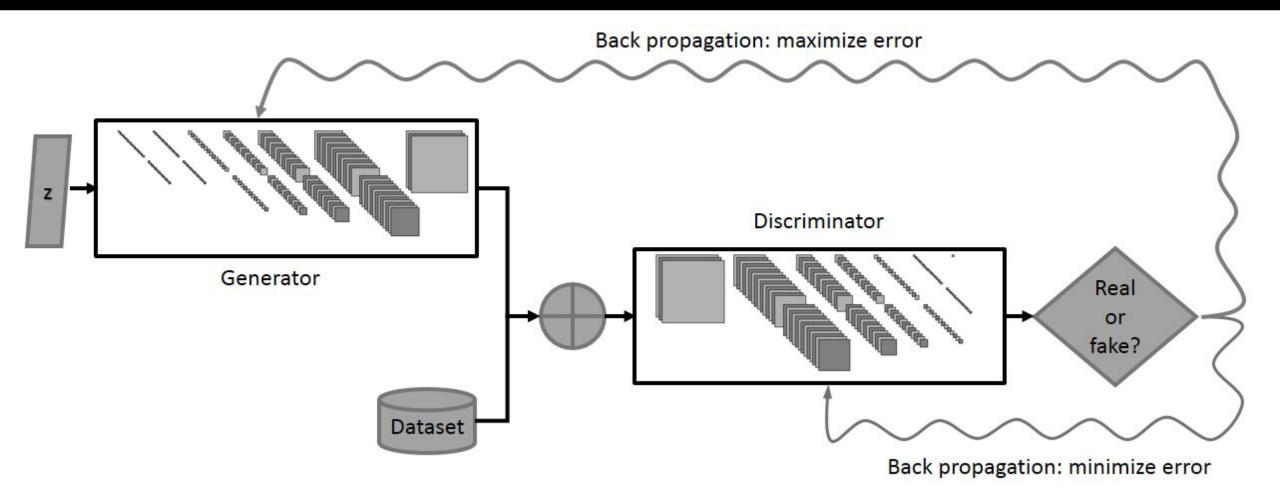


1D example of GAN





GANs in one image





Limitations of GANs (1/3)

- Mode Collapse: Generator does not generate the full range of plausible samples
- More likely if the generator is optimized while the discriminator is kept constant for many iterations



Limitations of GANs (2/3)

- GANs predict the entire sample (e.g. image) at once
- Difficult to predict pixel neighborhoods



Limitations of GANs (3/3)

- Difficult training process / convergence: Generator and discriminator keep oscillating
- Network does not converge to a stable, (near) optimal solution



Semi-supervised learning with GANs

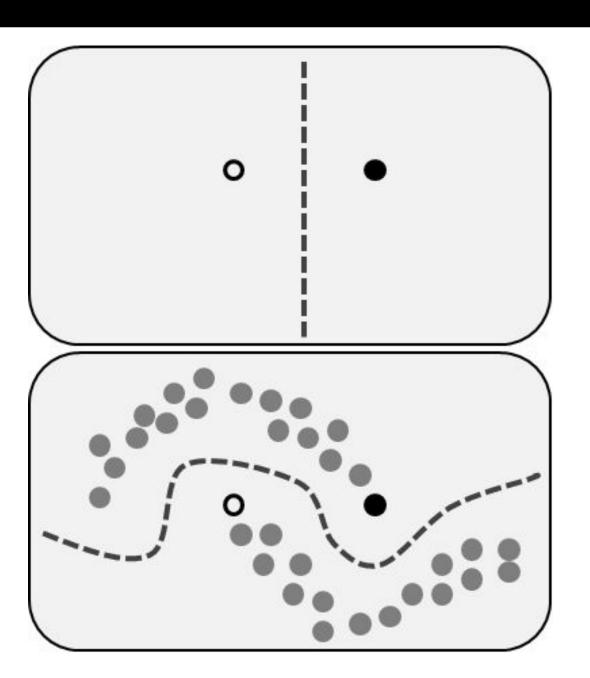


Why using GANs in a semi-supervised setting?

- Create a more diverse set of unlabeled data
- Get a better / more descriptive decision boundary
- Improve generalization when the amount of training samples is small



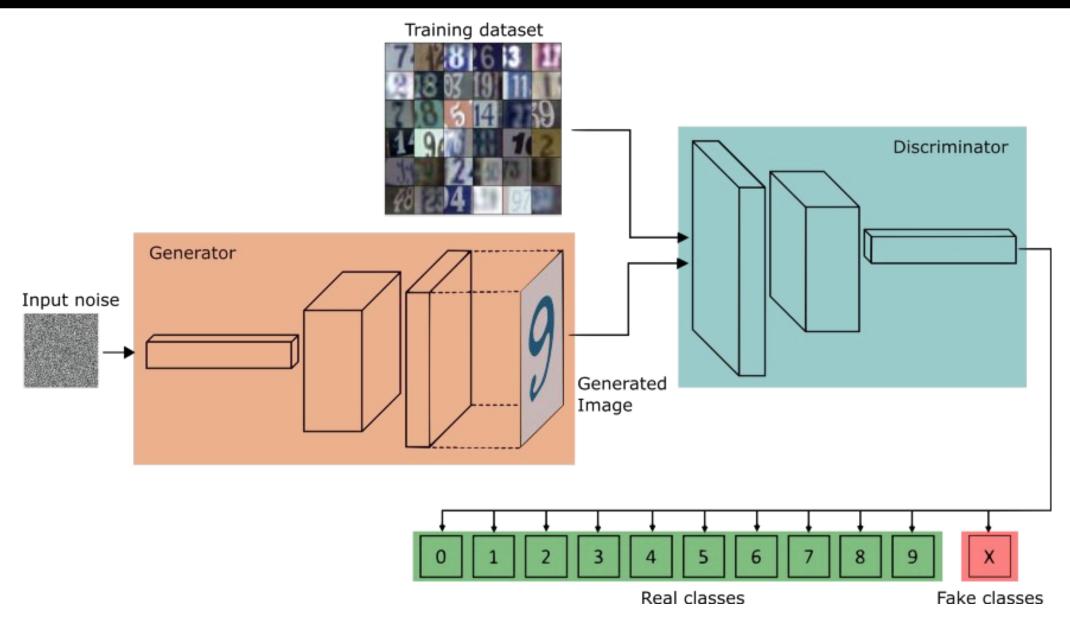
Influence of unlabeled data in semi-supervised learning



- Continuity assumption
- Cluster assumption
- Manifold assumption



Example of GAN in a semi-supervised learning role





Sources of information and their role for the discriminator

- Real samples that have labels, similar to normal supervised learning
- Real samples that do not have labels. For those, the discriminator only learns that these images are real
- Samples coming from the generator. For those, the discriminator learns to classify as fake



What do we have to modify to make it work?

- Adjust the loss functions so that we tackle both problems:
 - o as per the original GAN task, use binary cross entropy for the GAN part
 - as per multiclass classification task, use softmax cross entropy (or sparse cross entropy with logits) for the supervised task
 - apply masks to ignore the label not seen in the respective subtask
 - take the average of the GAN and supervised loss
- The discriminator can use the generator's images, as well as the labeled and unlabeled training data, to classify the dataset



Improving the GAN part

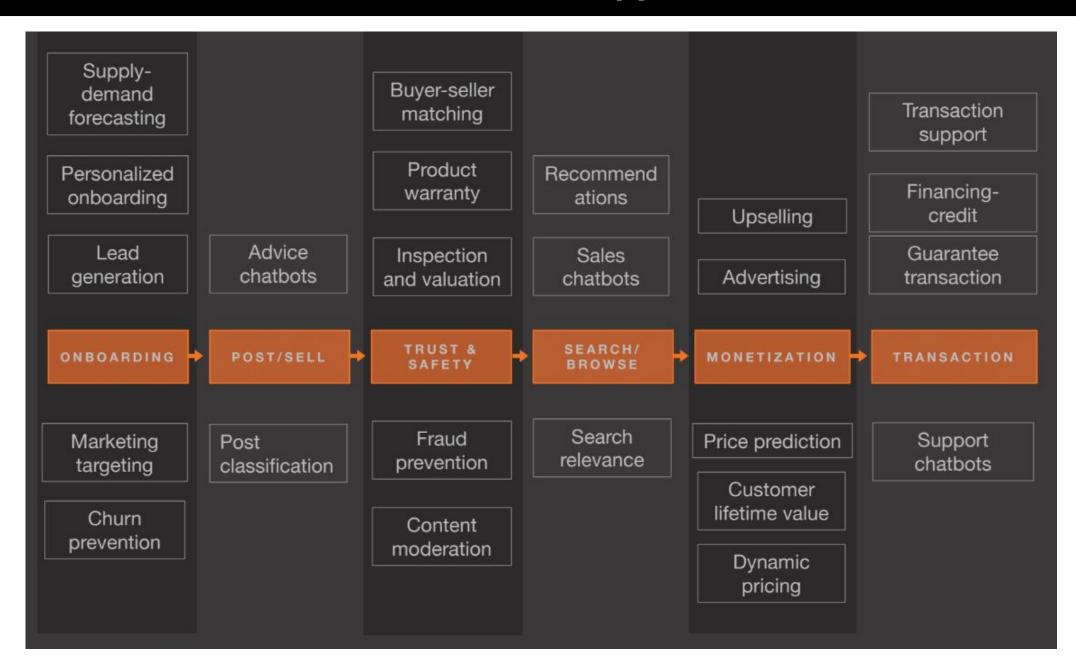
- Training GANs is a challenging problem -> feature matching approach
 - a. take the moments for some features for a "real" minibatch
 - b. take the moments for same features for a "fake" minibatch
 - c. minimize mean absolute error between the two



A use case from Trust and Safety



Classifieds - Data Science areas of Application





Classifieds - Data Science areas of Application

- Spam can be a problem in open platforms like classifieds
- Its annoying and can also be used as a vehicle for fraud
- How can we keep bad users out without annoying good users with stringent policies?

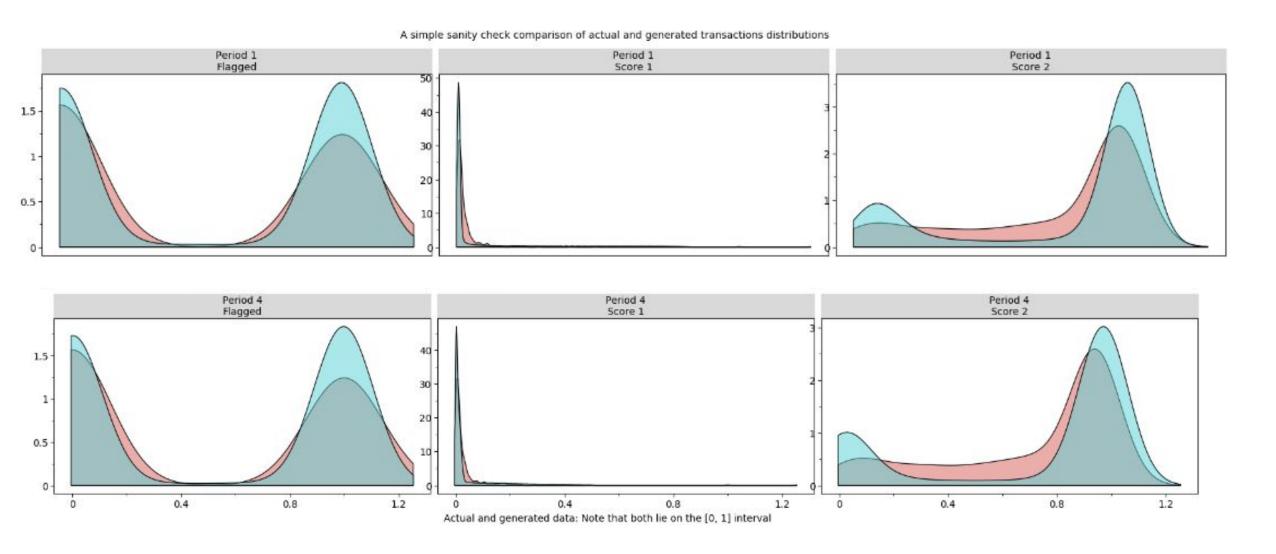


Why is it a challenge?

- It's a recurring battle, with spammers becoming more inventive to circumvent the algorithms
- We may have only a few cases of cases of annotated examples for certain types of bad content



Generating Synthetic Samples with GANs





Results

- In the presented example we only have a few tens of a certain type of spam
- We are able to quickly explore the input space and map to a latent space combining the different types of signal we have available from text, image, user behaviour, etc.
- Semi supervised learning with GANs does better (AUC = 99.9) vs Random Forest (AUC = 99.7)



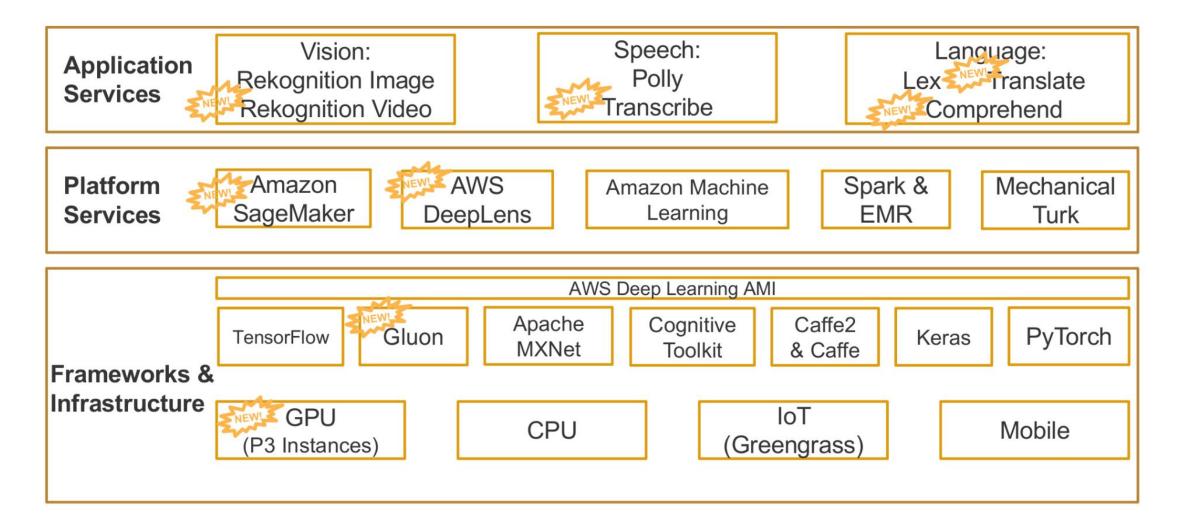


Questions and Discussion

Model Deployment Options - Making endpoints

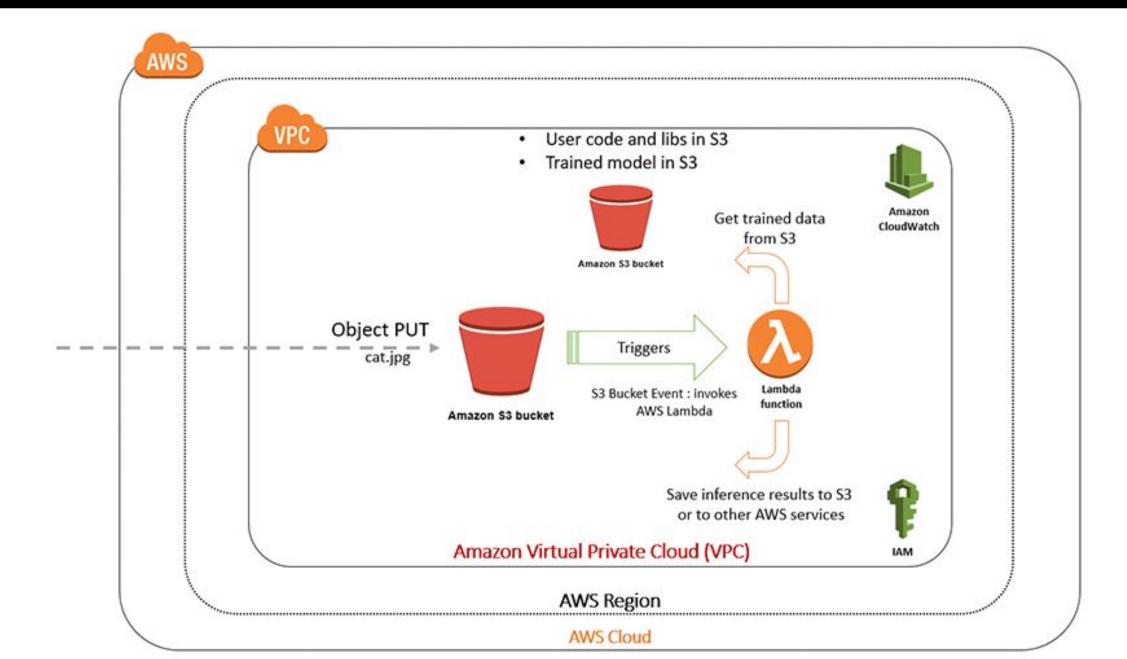


AWS Sagemaker in the ML Stack





AWS Lambda with Tensorflow





Resources

- Using Chalice to serve SageMaker predictions
 - https://medium.com/@julsimon/using-chalice-to-serve-sagemaker-predictions-a2015c02b033
- SageMaker examples
 - https://github.com/awslabs/amazon-sagemaker-examples
- How to Deploy Deep Learning Models with AWS Lambda and Tensorflow
 - https://aws.amazon.com/blogs/machine-learning/how-to-deploy-deep-learning-models-with-aws-lambda-and-tensorflow/

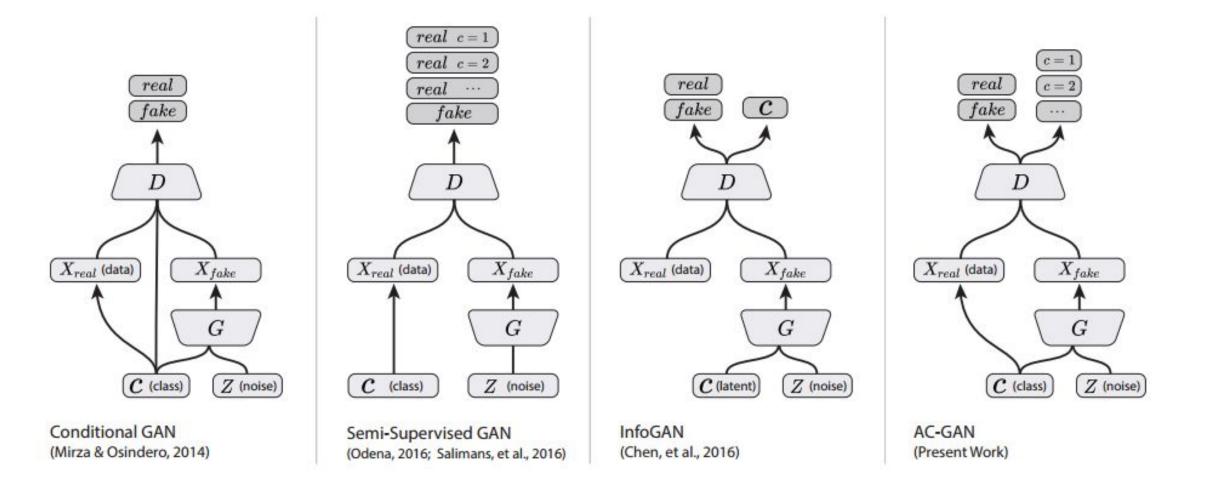


References

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- Semi-supervised learning with Generative Adversarial Networks (GANs)
 - https://towardsdatascience.com/semi-supervised-learning-with-gans-9f3cb128c5e
- CNNs, three things you need to know
 - https://www.mathworks.com/solutions/deep-learning/convolutional-neural-network.html
- Semi-supervised learning
 - https://en.wikipedia.org/wiki/Semi-supervised_learning
- Variants of GANs
 - https://www.slideshare.net/thinkingfactory/variants-of-gans-jaejun-yoo
- From GAN to WGAN
 - https://lilianweng.github.io/lil-log/2017/08/20/from-GAN-to-WGAN.html



Types of GANs





Deployment Options we will discuss

Amazon Sagemaker

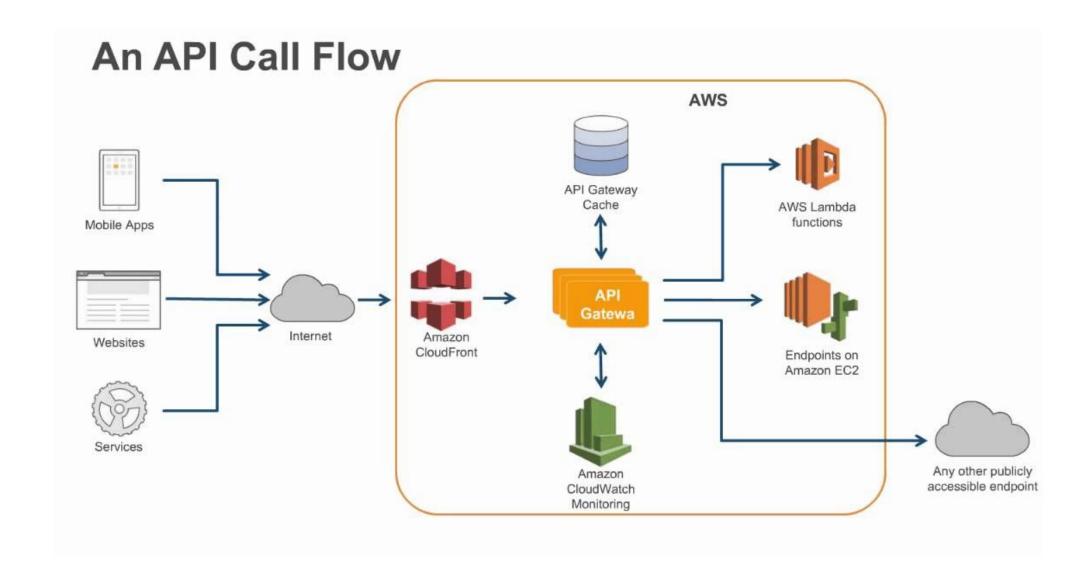
AWS Lambda and Tensorflow



Amazon SageMaker



A fully managed service that enables data scientists and developers to quickly and easily build machine-learning based models into production smart applications.

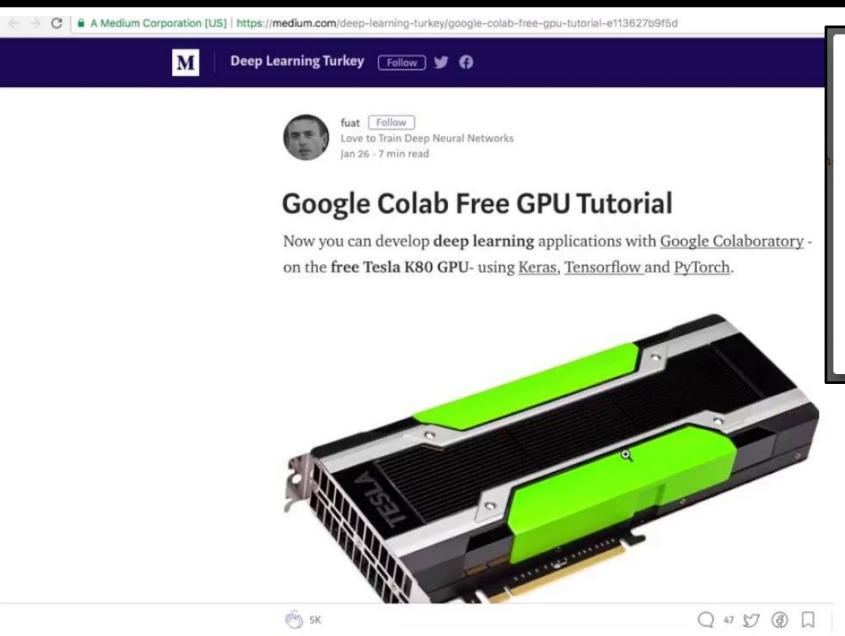


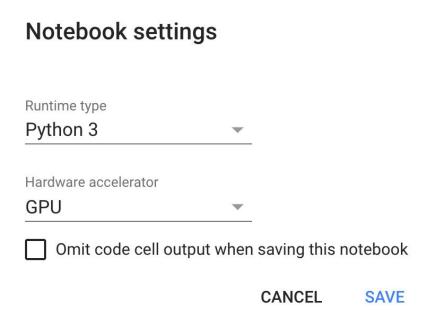


Google Colaboratory



Google Colaboratory: Tensorflow + GPU + GDrive + Notebook + Free











Google Colaboratory

- What is Google Colaboratory?
- Tensorflow + GPU + GDrive + Notebook + Free
- Free (limited) use of GPUs for training



Interface - Show me the code

