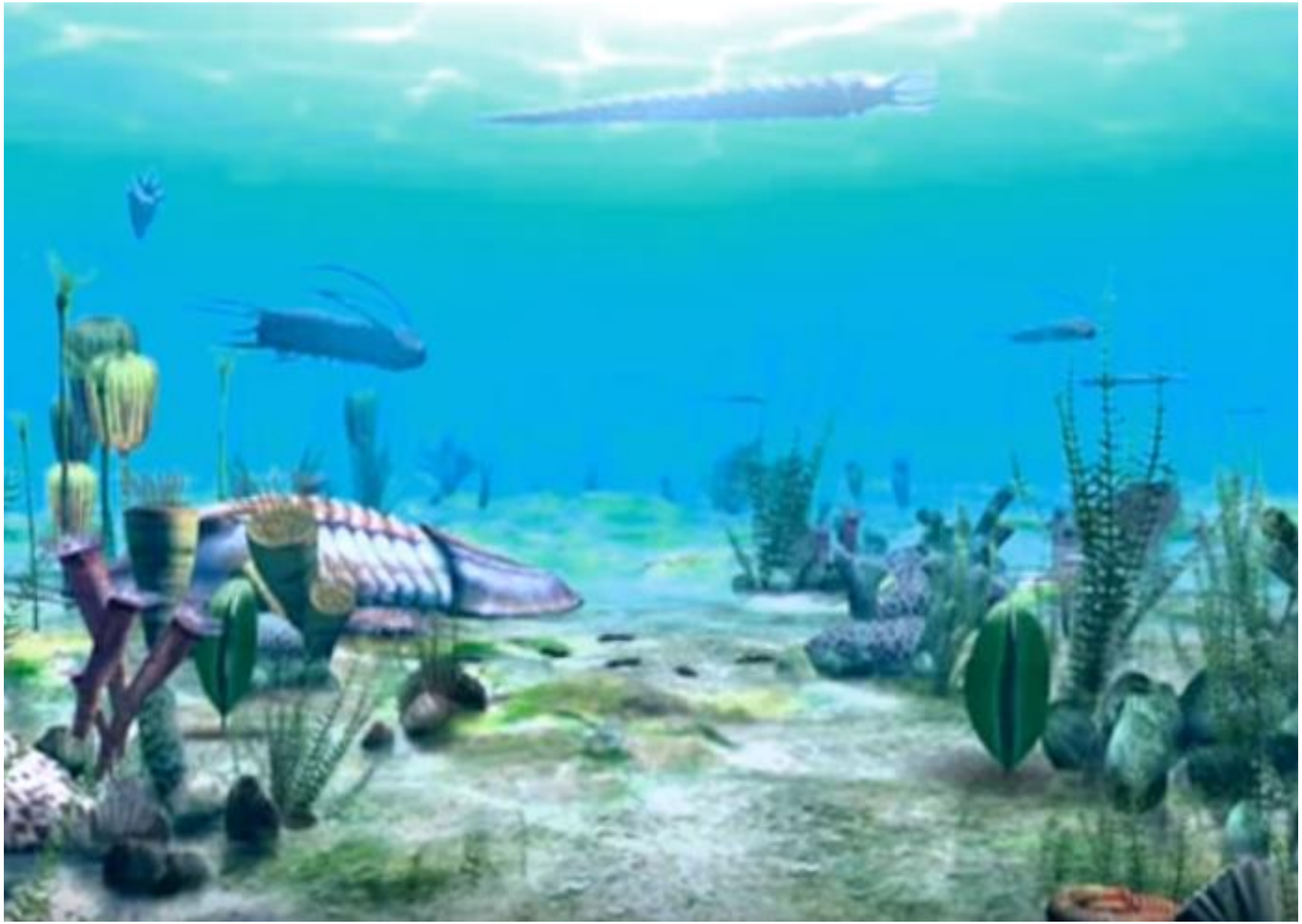
Generative Adversarial Network

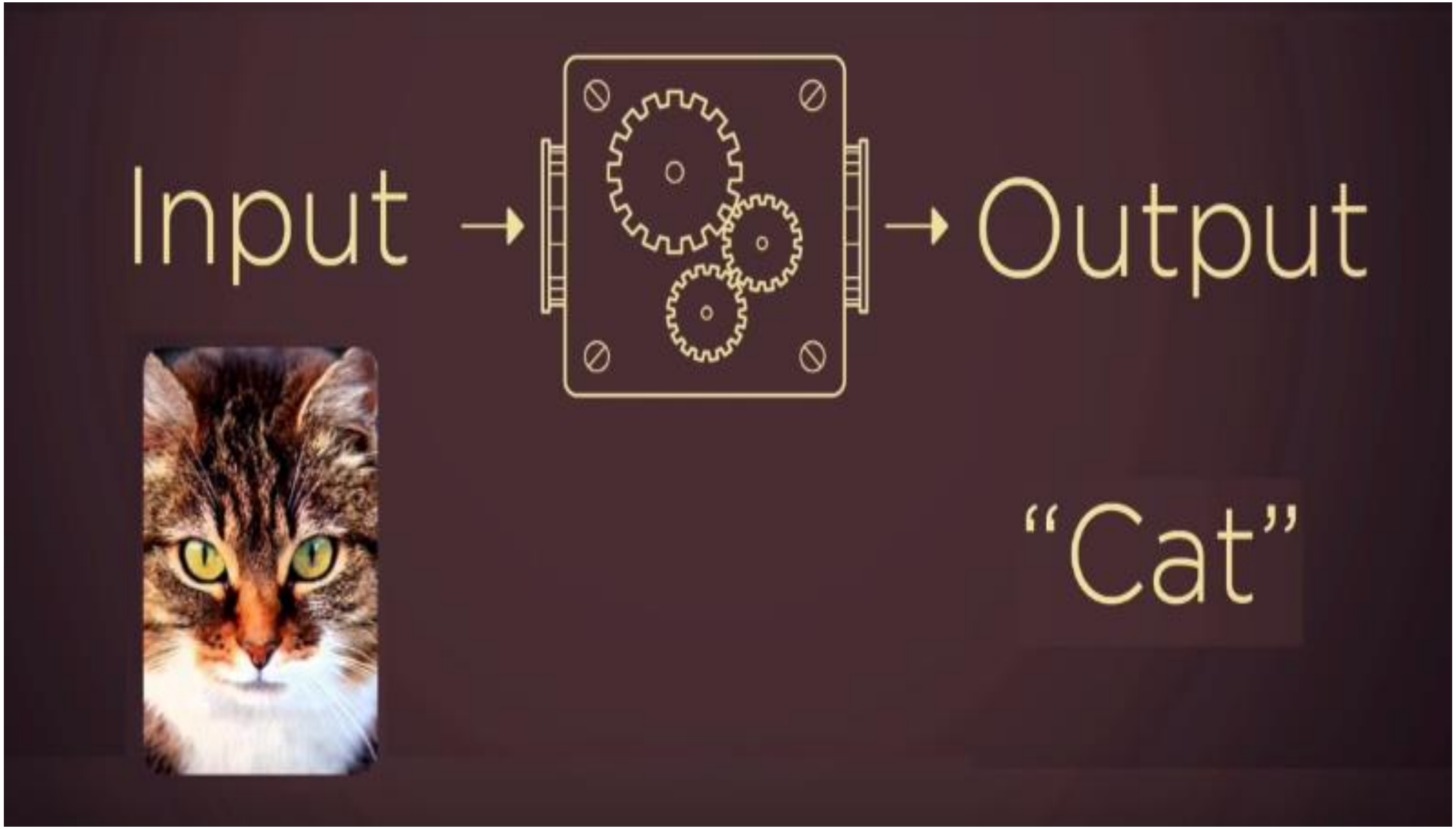
Mohsen Porouhan

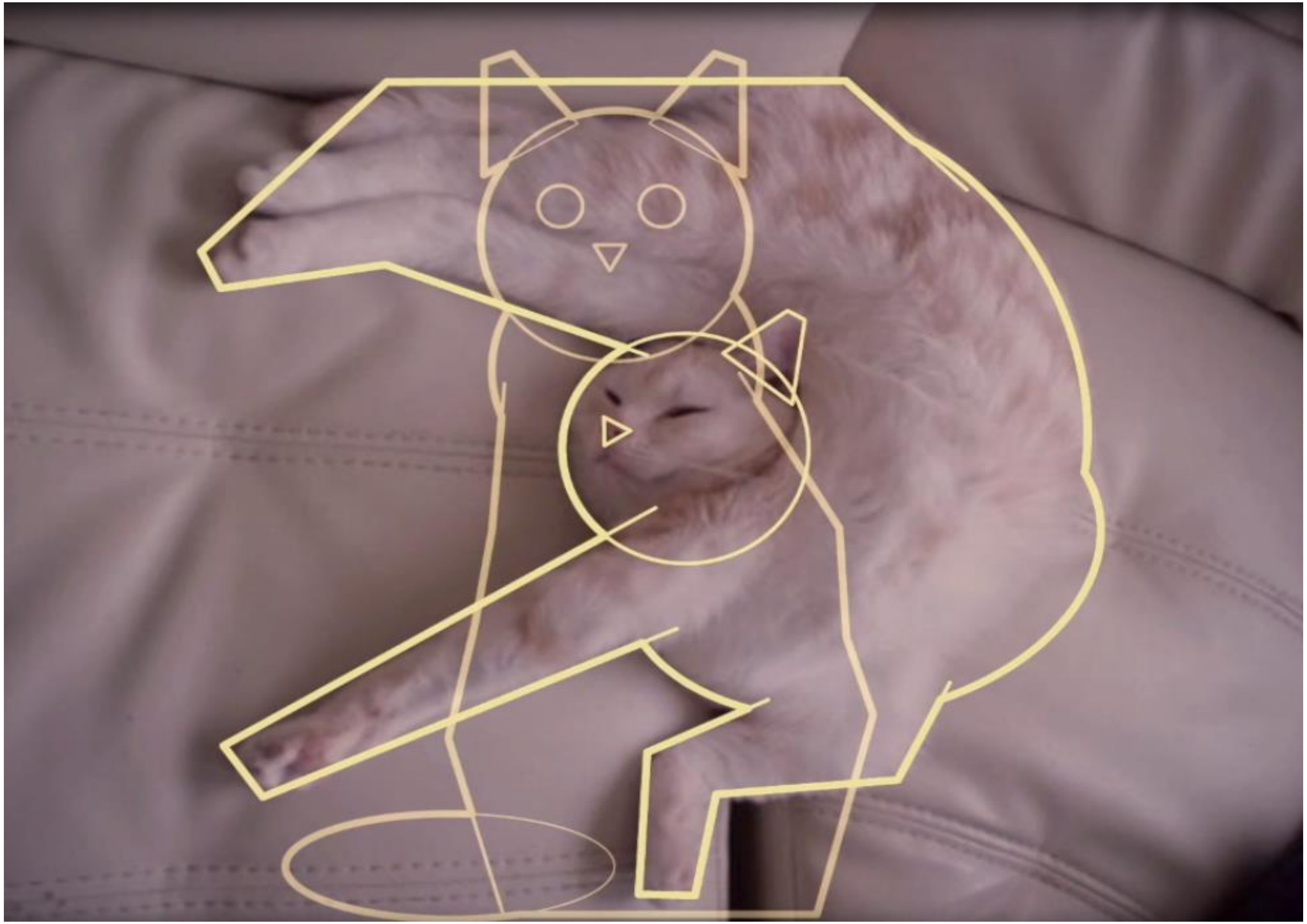
Prof: Dr Zahra Zojaji

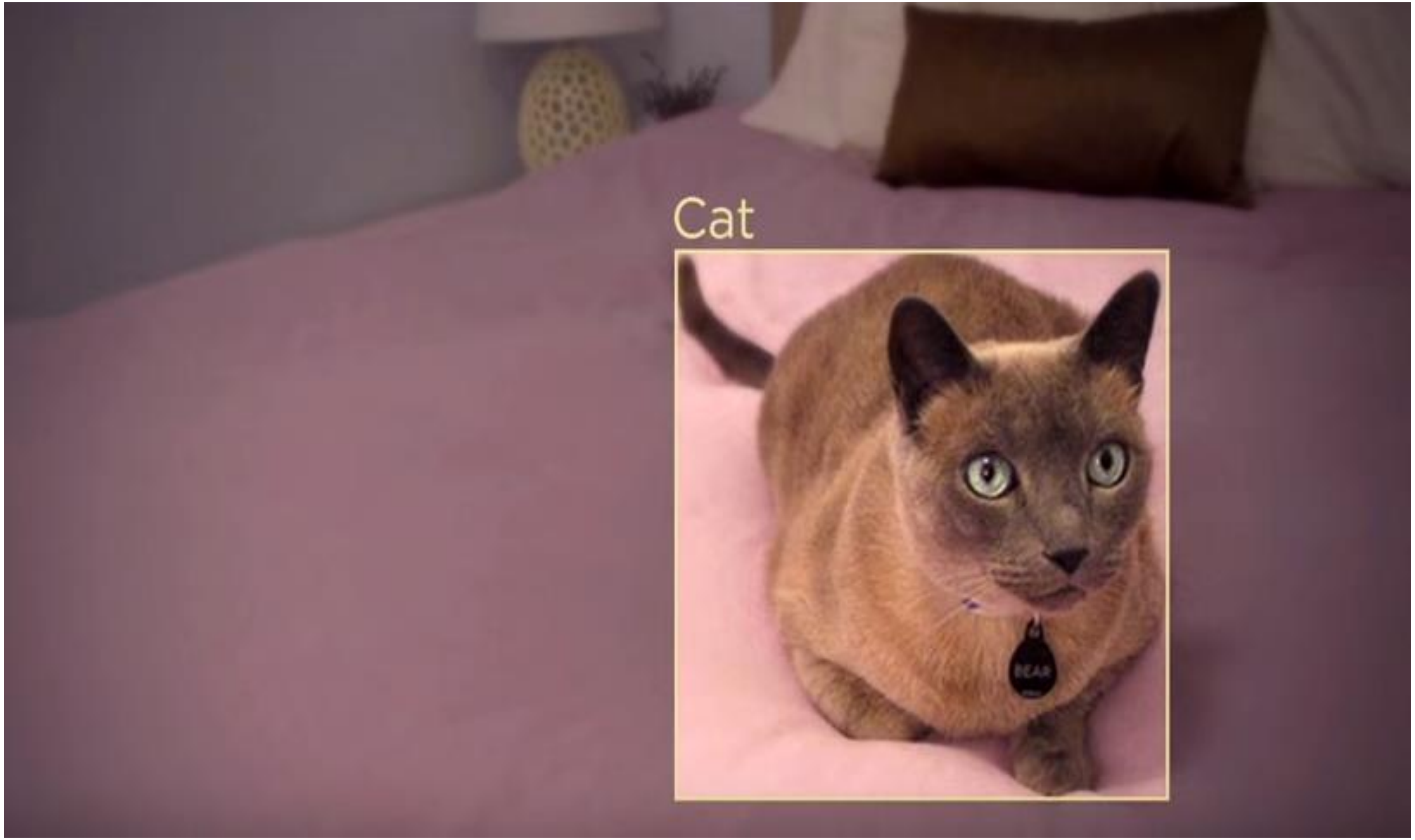


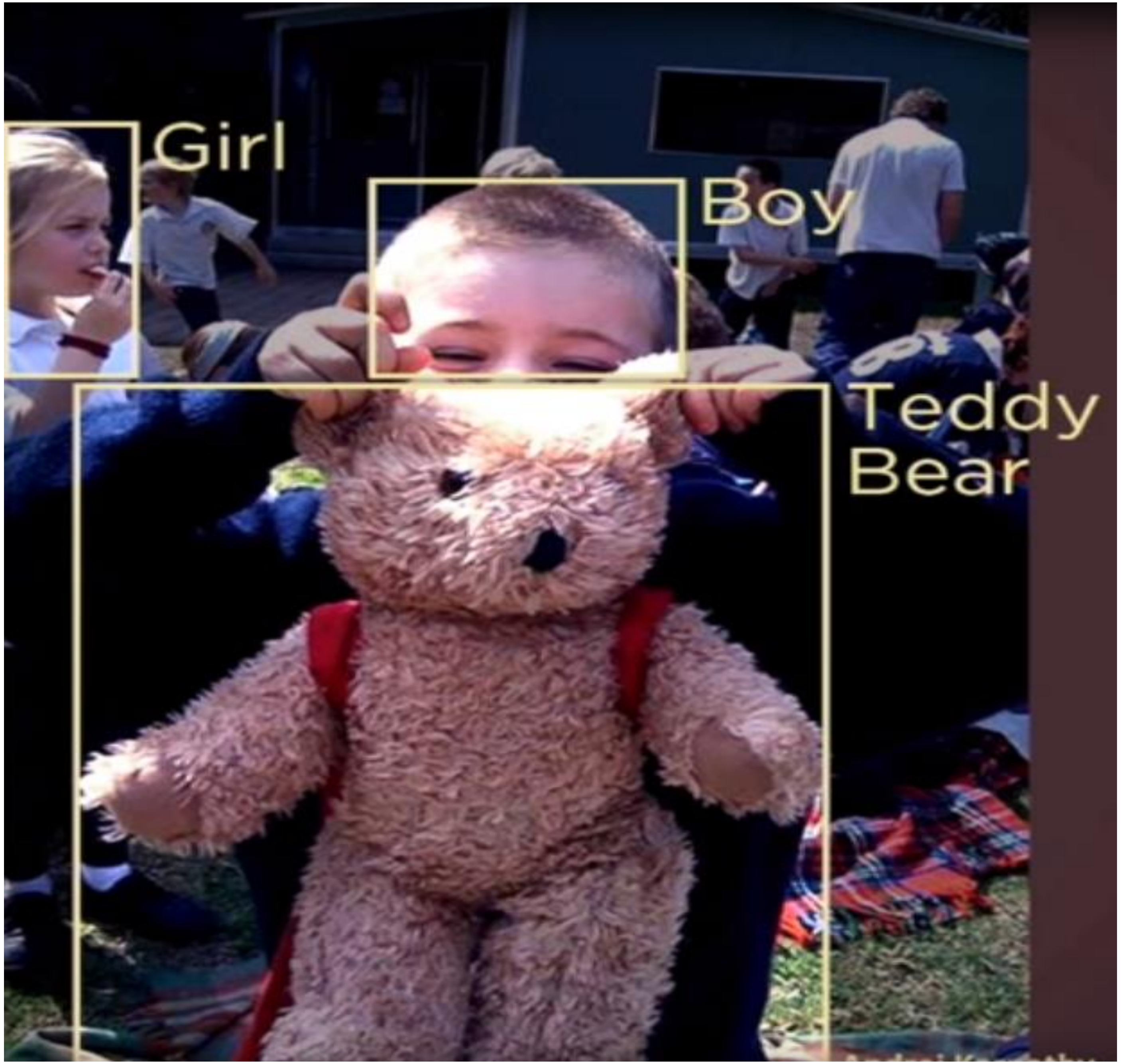

HELP
MEDICAL

Computer vision:
Shining light on the digital word

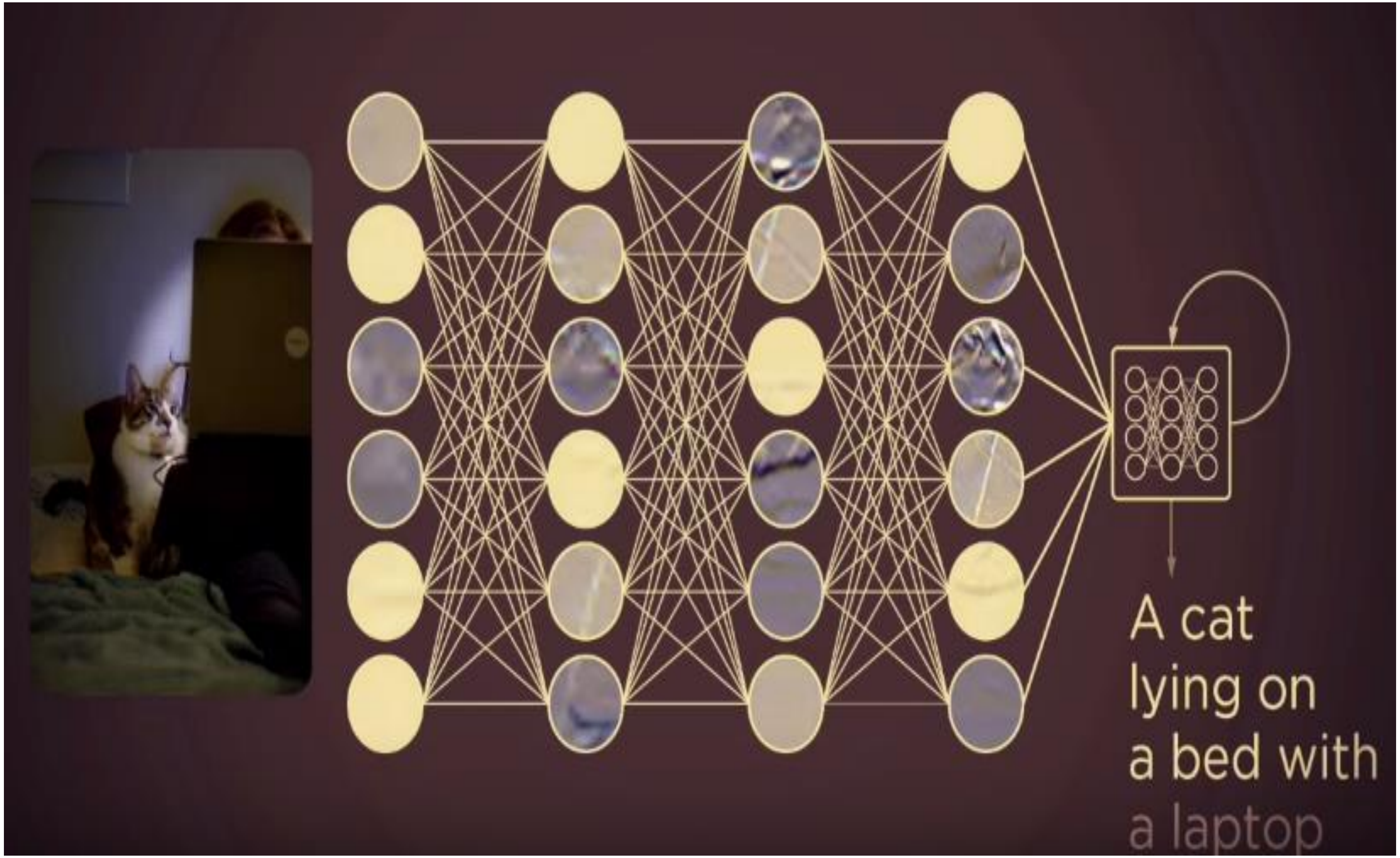

Input
Output
"Cat"




Cat

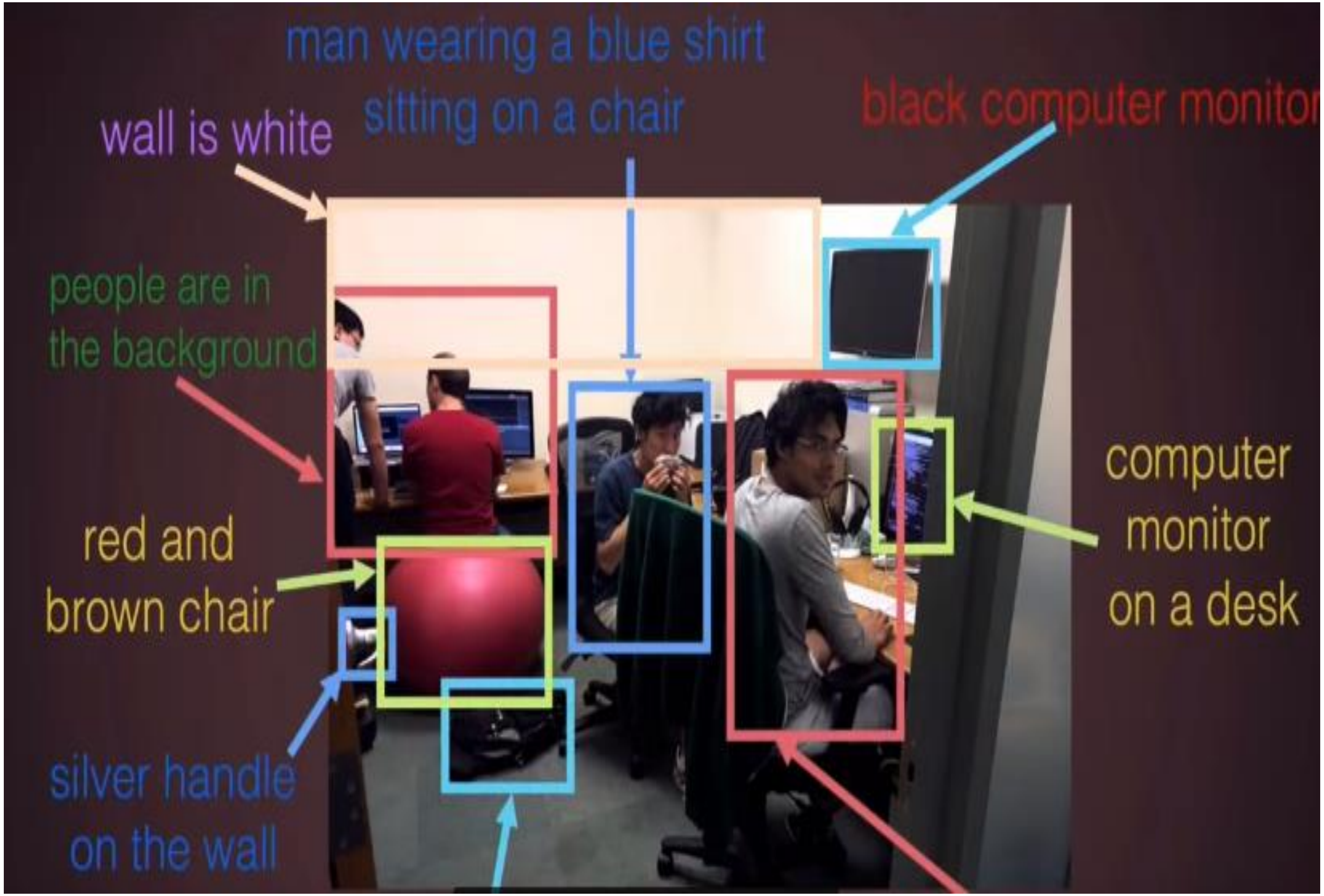

Girl
Boy
Teddy
Bear

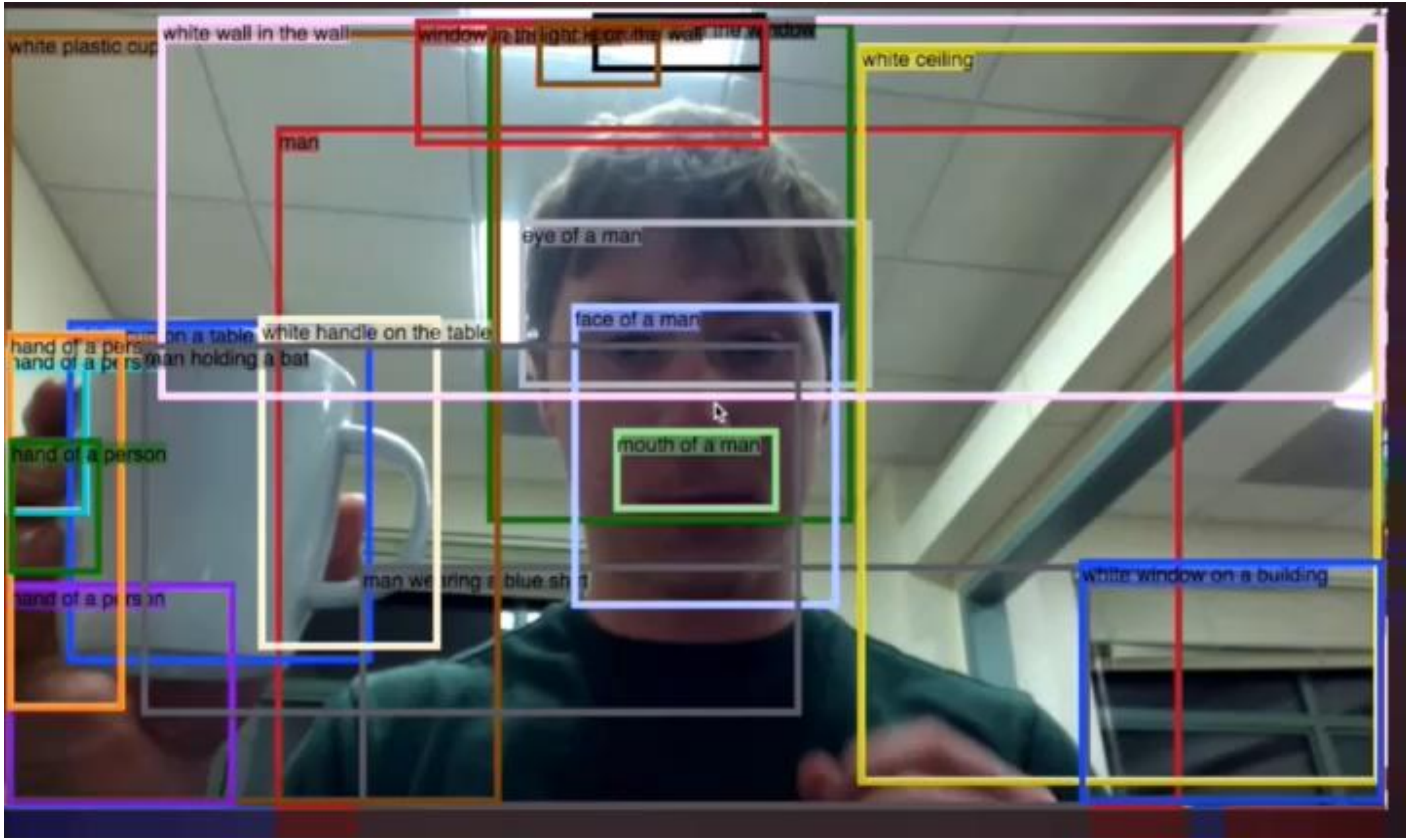

Kite
Person
Dog


A cat
lying on
a bed with
a laptop

"a large airplane sitting on top of an airport runway"


"a man is standing next
to an elephant"


man wearing a blue shirt
sitting on a chair
wall is white
black computer monitor
people are in
the background
computer
monitor
on a desk
red and
brown chair
silver handle
on the wall


white plastic cup
white wall in the wall
white ceiling
man
eye of a man
white handle on the table
face of a man
man holding a bat
hand of a person
mouth of a man
white window on a building

Supervised vs Unsupervised Learning

Supervised Learning

Data: (x, y)

x is data, y is label

Goal: Learn a *function* to map x -> y

Examples: Classification, regression, object detection, semantic segmentation, image captioning, etc.

Supervised vs Unsupervised Learning

Unsupervised Learning

Data: x

Just data, no labels!

Goal: Learn some underlying hidden *structure* of the data

Examples: Clustering, dimensionality reduction, feature learning, density estimation, etc.

Generative Models

Given training data, generate new samples from same distribution

Training data ~ pdata(x)

Generated samples ~ pmodel(x)

Want to learn pmodel(x) similar to pdata(x)

Taxonomy of Generative Models

Today: discuss 3 most popular types of generative models today

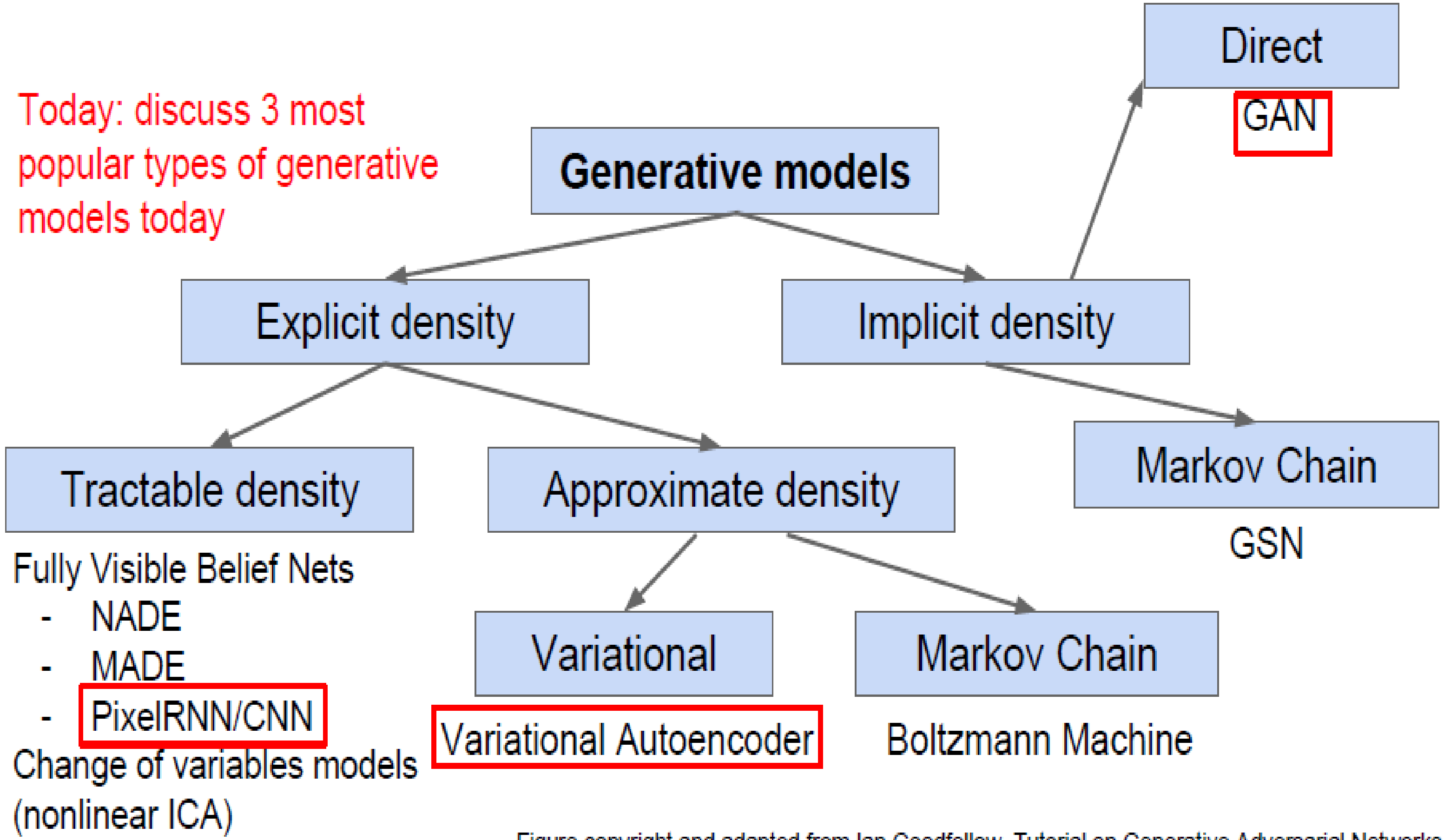
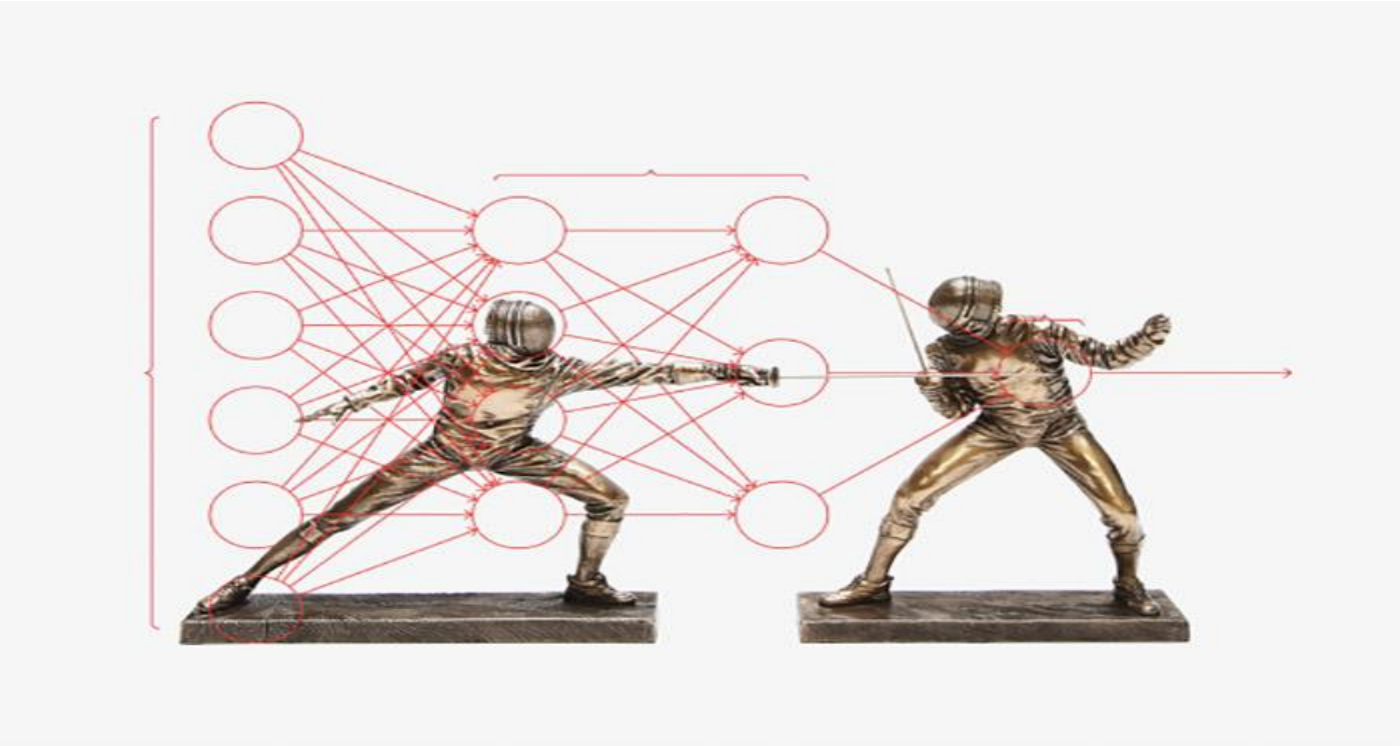


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

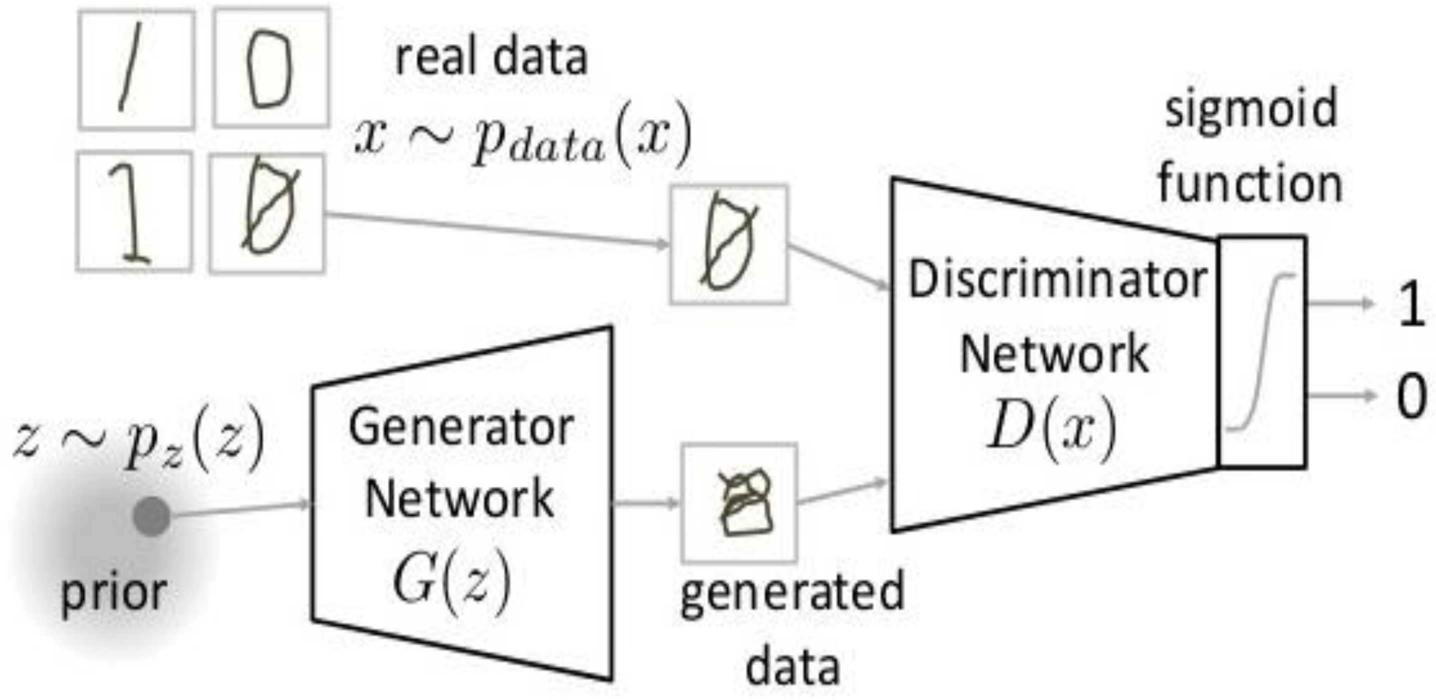
Generative Adversarial Networks

Generator network: try to fool the discriminator by generating real-looking images

Discriminator network: try to distinguish between real and fake images



How do GANs work?



Mathematical representation of GAN

$$\min_{G} \max_{D} V(D, G)$$

$$V(D, G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

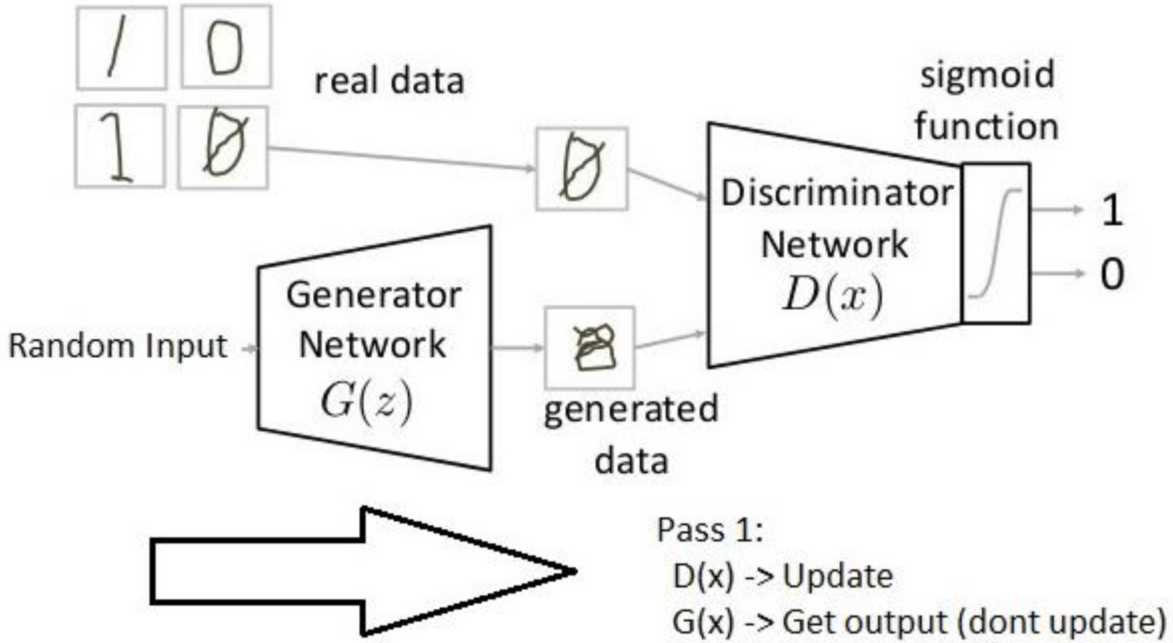
notations we use to formalize our GAN:

Pdata(x) -> the distribution of real data
X -> sample from pdata(x)
P(z) -> distribution of generator
Z -> sample from p(z)
G(z) -> Generator Network
D(x) -> Discriminator Network

Parts of training GAN

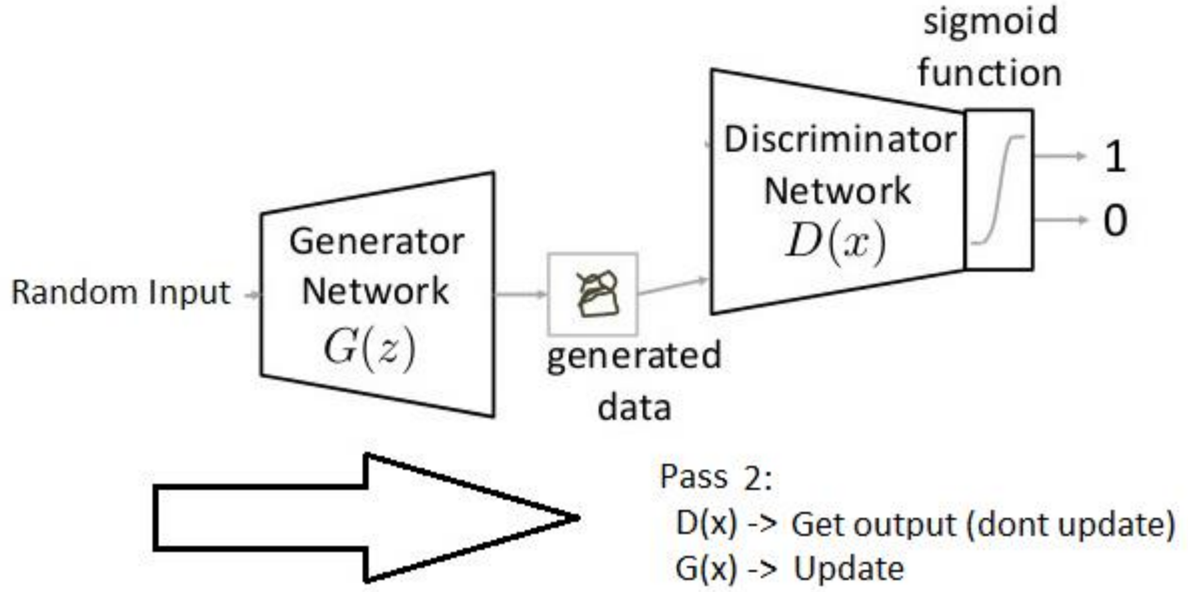
Train discriminator and freeze generator

freezing means setting training as false



Parts of training GAN

Train generator and freeze discriminator



Steps to train a GAN

Step 1: Define the problem

Step 2: Define architecture of GAN

Step 3: Train Discriminator on real data for n epochs

Step 4: Generate fake inputs for generator and train discriminator on fake data

Step 5: Train generator with the output of discriminator

Step 6: Repeat step 3 to step 5 for a few epochs

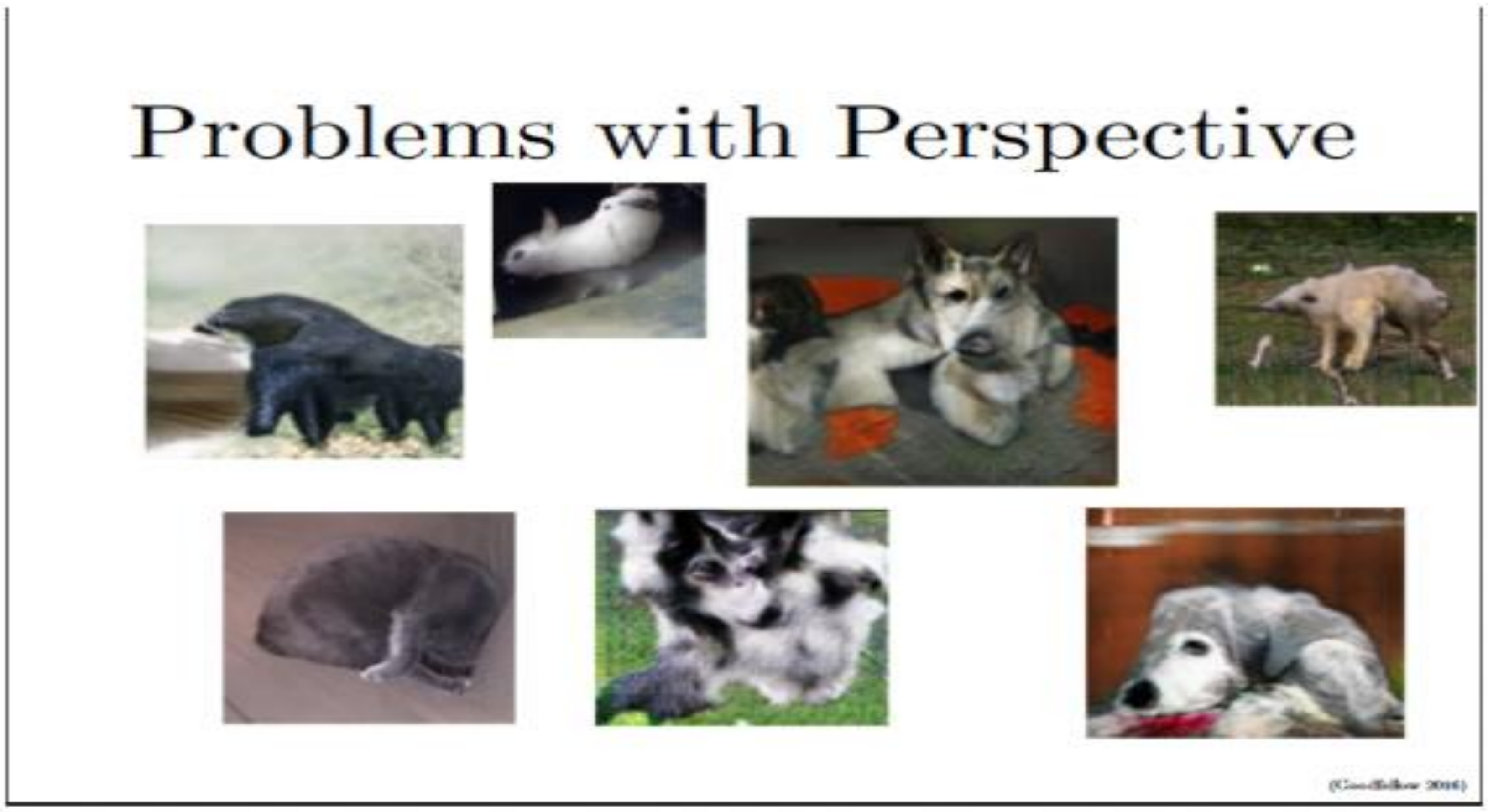
Step 7: Check if the fake data manually if it seems legit. If it seems appropriate, stop training, else go to step 3

Challenges with GANs

Both generator and discriminator are fighting against each other to get one step ahead of the other. Also, they are dependent on each other for efficient training. If one of them fails, the whole system fails. So you have to make sure they don't explode.

Problem with Counting

Problems with Perspective



Problems with Global Structures

A substantial research is being done to take care of these problems. Newer types of models are proposed which give more accurate results than previous techniques, such as DCGAN, WassersteinGAN etc

Implementing

You need to setup the libraries

numpy

pandas

tensorflow

keras

keras_adversarial

“The GAN Zoo”

See also: https://github.com/soumith/ganhacks for tips and tricks for trainings GANs

- GAN - Generative Adversarial Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- AdaGAN - AdaGAN: Boosting Generative Models
- AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
- AffGAN - Amortised MAP Inference for Image Super-resolution
- AL-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
- ALI - Adversarially Learned Inference
- AM-GAN - Generative Adversarial Nets with Labeled Data by Activation Maximization
- AnoGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
- ArtGAN - ArtGAN: Artwork Synthesis with Conditional Categorial GANs
- b-GAN - b-GAN: Unified Framework of Generative Adversarial Networks
- Bayesian GAN - Deep and Hierarchical Implicit Models
- BEGAN - BEGAN: Boundary Equilibrium Generative Adversarial Networks
- BiGAN - Adversarial Feature Learning
- BS-GAN - Boundary-Seeking Generative Adversarial Networks
- CGAN - Conditional Generative Adversarial Nets
- CaloGAN - CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks
- CCGAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
- CatGAN - Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks
- CoGAN - Coupled Generative Adversarial Networks
- Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning Diagram Generation
- C-RNN-GAN - C-RNN-GAN: Continuous recurrent neural networks with adversarial training
- CS-GAN - Improving Neural Machine Translation with Conditional Sequence Generative Adversarial Nets
- CVAE-GAN - CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training
- CycleGAN - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks
- DTN - Unsupervised Cross-Domain Image Generation
- DCGAN - Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks
- DiscoGAN - Learning to Discover Cross-Domain Relations with Generative Adversarial Networks
- DR-GAN - Disentangled Representation Learning GAN for Pose-Invariant Face Recognition
- DualGAN - DualGAN: Unsupervised Dual Learning for Image-to-Image Translation
- EBGAN - Energy-based Generative Adversarial Network
- f-GAN - f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization
- FF-GAN - Towards Large-Pose Face Frontalization in the Wild
- GAWWN - Learning What and Where to Draw
- GeneGAN - GeneGAN: Learning Object Transfiguration and Attribute Subspace from Unpaired Data
- Geometric GAN - Geometric GAN
- GoGAN - Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking
- GP-GAN - GP-GAN: Towards Realistic High-Resolution Image Blending
- IAN - Neural Photo Editing with Introspective Adversarial Networks
- iGAN - Generative Visual Manipulation on the Natural Image Manifold
- IcGAN - Invertible Conditional GANs for image editing
- ID-CGAN - Image De-raining Using a Conditional Generative Adversarial Network
- Improved GAN - Improved Techniques for Training GANs
- InfoGAN - InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets
- LAGAN - Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis
- LAPGAN - Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks

https://github.com/hindupuravinash/the-gan-zoo

Application of GAN

https://phillipi.github.io/pix2pix/

https://affinelayer.com/pixsrv/

https://phillipi.github.io/pix2pix/images/map2sat1_BtoA/latest_net_G_val/index.html

https://phillipi.github.io/pix2pix/images/index_cityscapes_loss_variations.html\

Increasing Resolution of an image

Interactive Image Generation

Text to Image Generation

…