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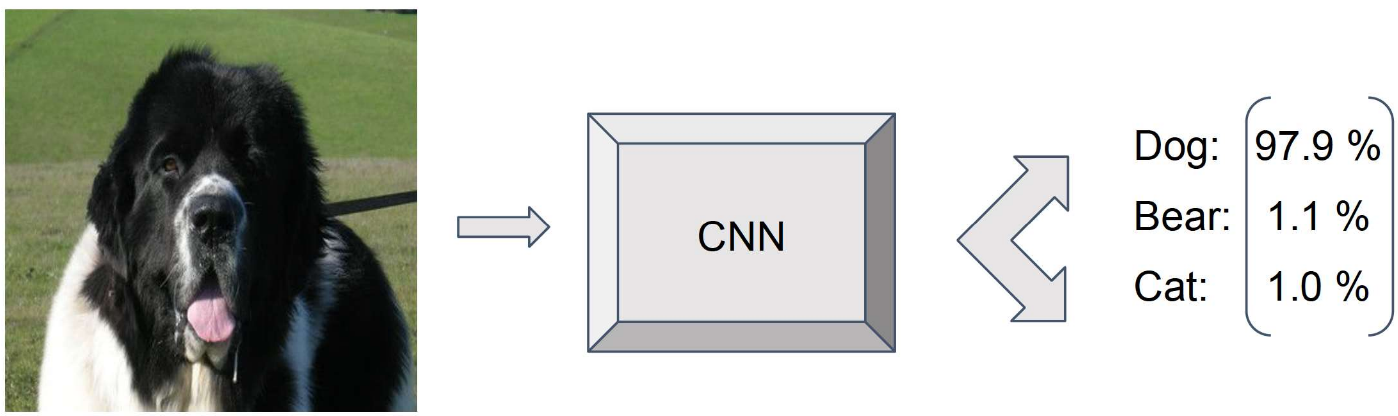
CNN Applications

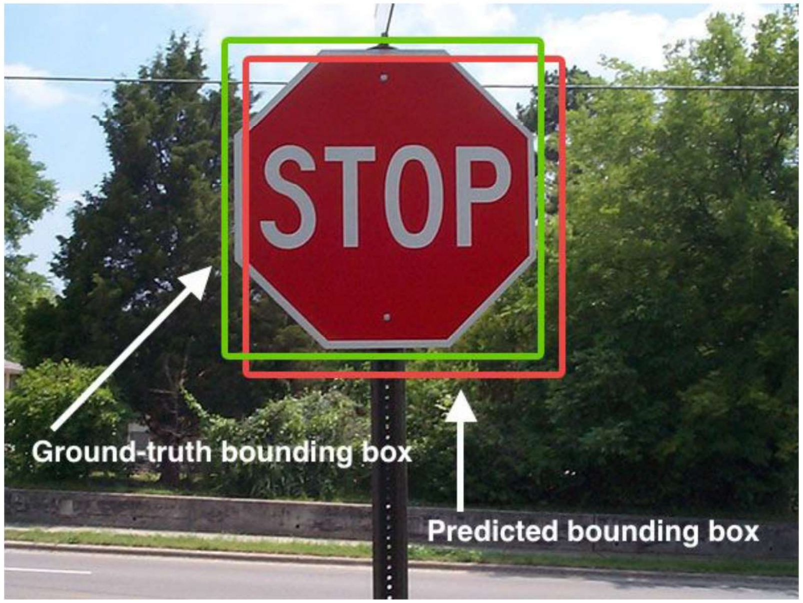
Image Classification

Image classification can be defined as “given an image, what category does the image belong to?”. CNNs are not the only way to do this but happen to be very good at it. This is the most commonly used task for CNNs.



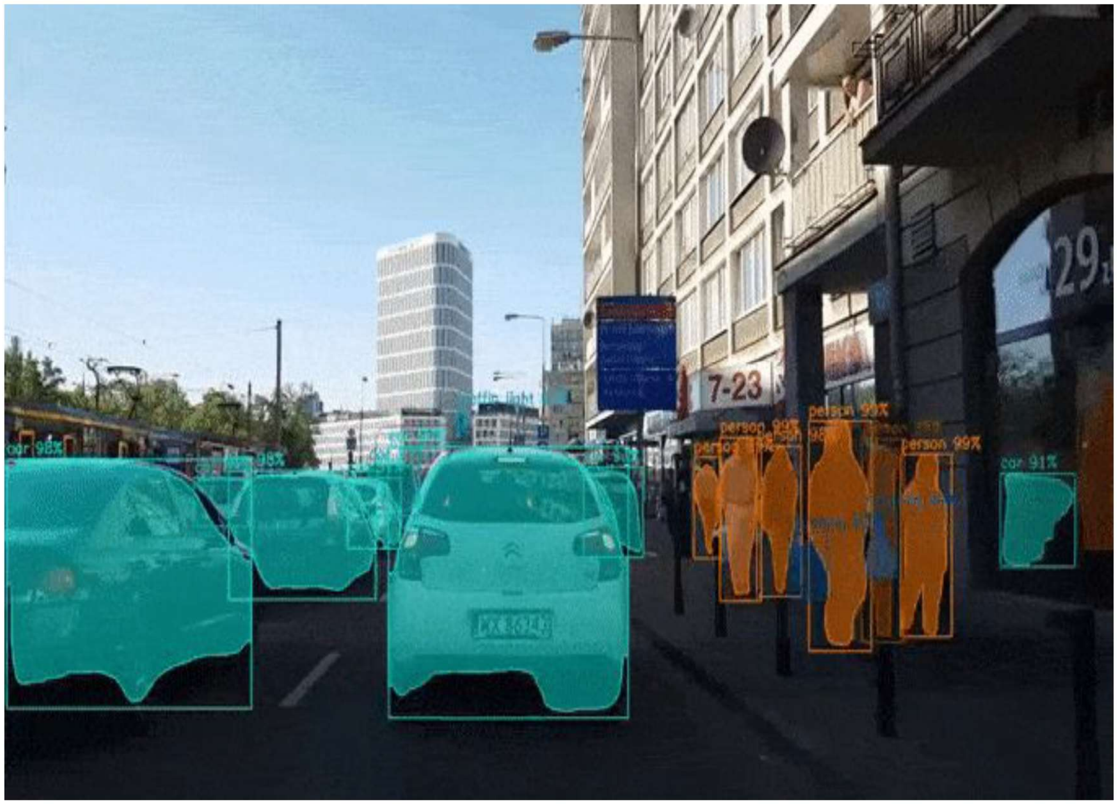
Object Detection

In object detection, coordinates to a bounding box are predicted, as well as the category of object the box belongs to.



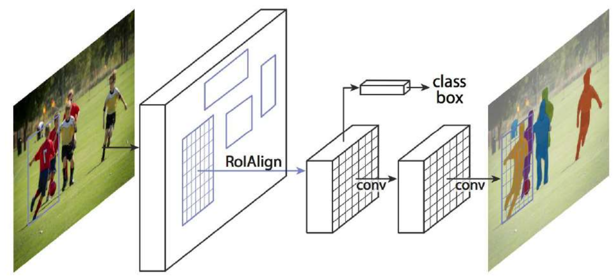
https://upload.wikimedia.org/wikipedia/commons/2/2d/Intersection_over_Union_-_object_detection_bounding_boxes.jpg

Image Segmentation



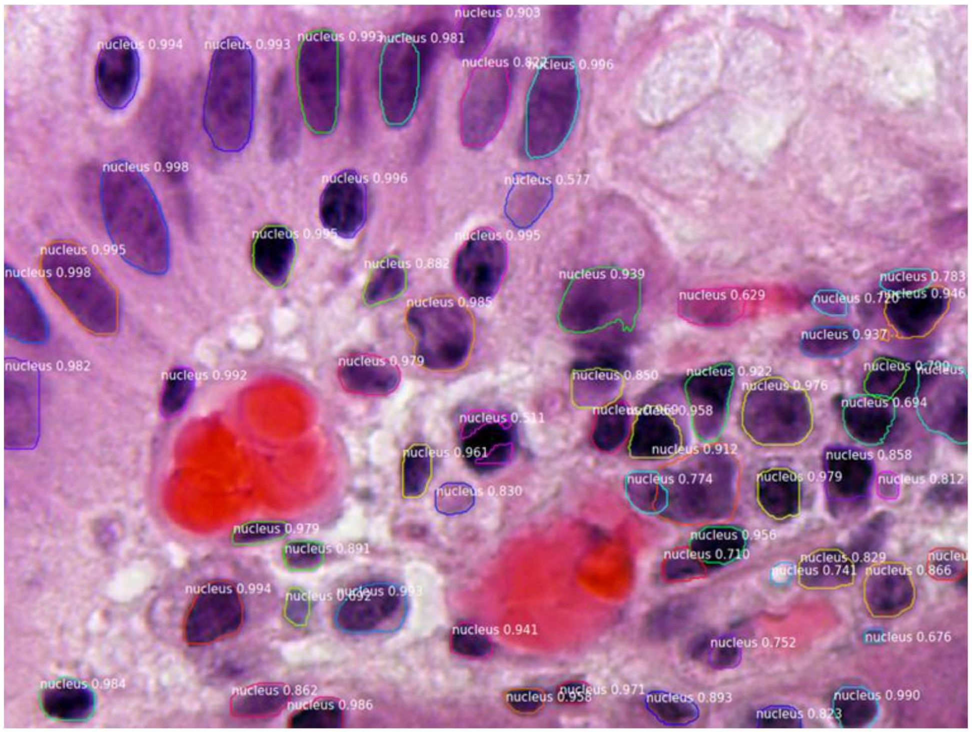
https://github.com/matterport/Mask_RCNN

Image segmentation is the next logical step in object detection; it determines which pixels correspond to the detected objects.



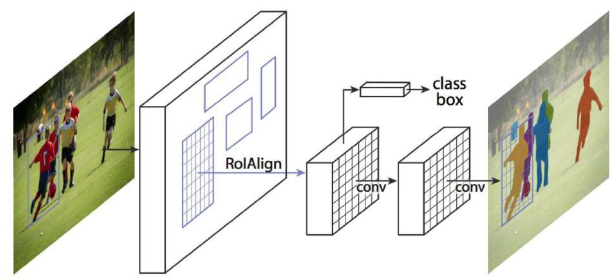
Mask RCNN Architecture

Image Segmentation



https://github.com/matterport/Mask_RCNN

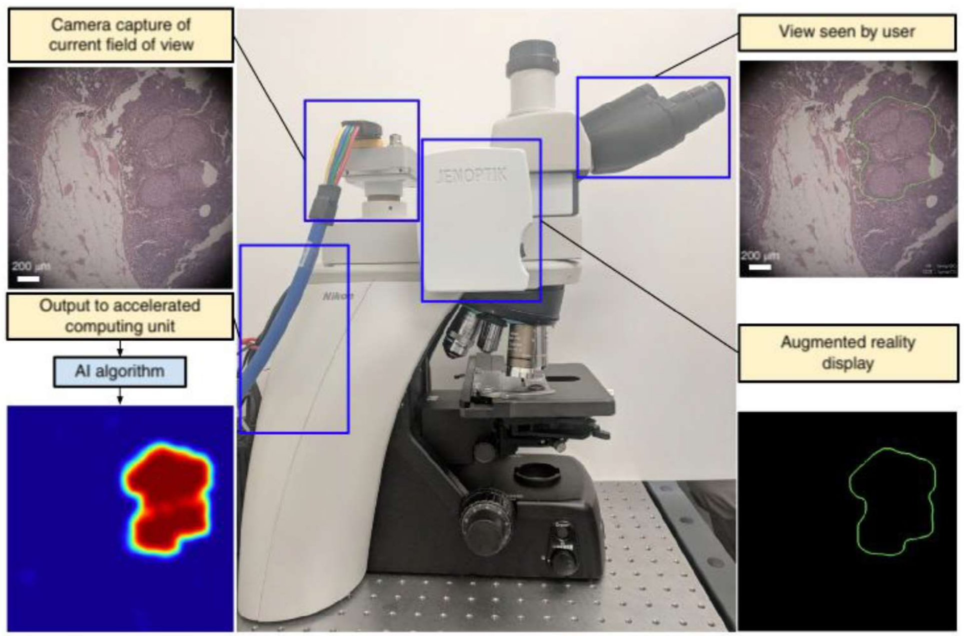
It can be used in a wide variety of fields, such as medical imaging.



Mask RCNN Architecture

Augmented (Medical) Reality

Here is an example of a microscope rendering in real-time regions of interest in medical images.



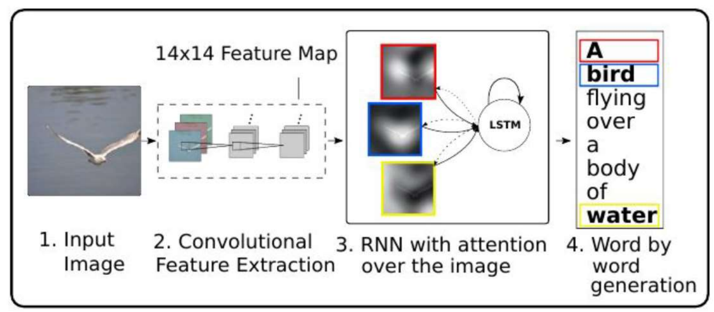
source

Caption Generation

CNNs can be used in a pipeline (along with other NLP models) to help models learn to generate captions.

A woman is throwing a frisbee in a park.

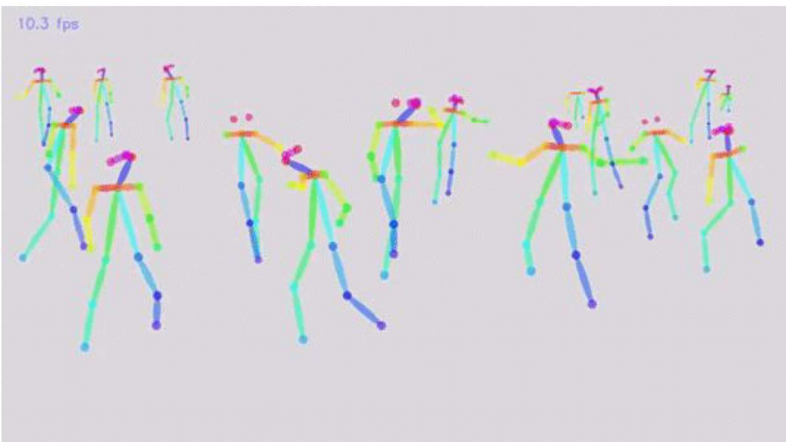
Figure 1. Our model learns a words/image alignment. The visualized attentional maps (3) are explained in Sections 3.1 & 5.4



https://arxiv.org/pdf/1502.03044.pdf

Human Pose Estimation

It is possible to use CNNs to extract human poses from images

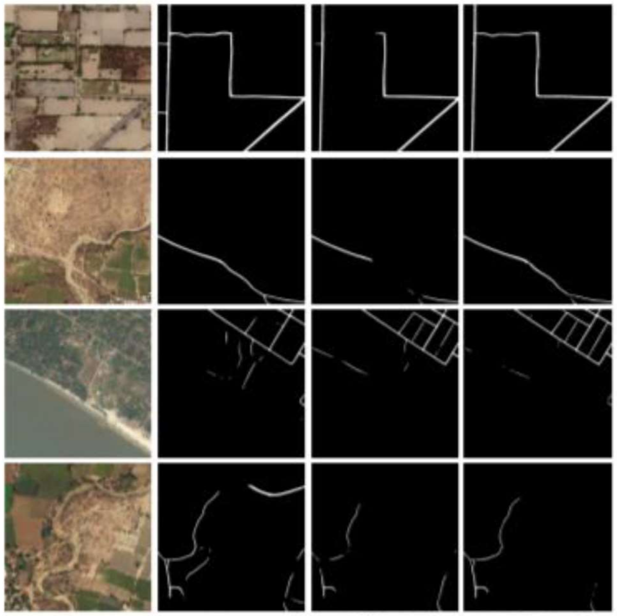


https://github.com/rachit2403/Open-Pose-Keras

https://github.com/facebookresearch/DensePose

Road Mapping

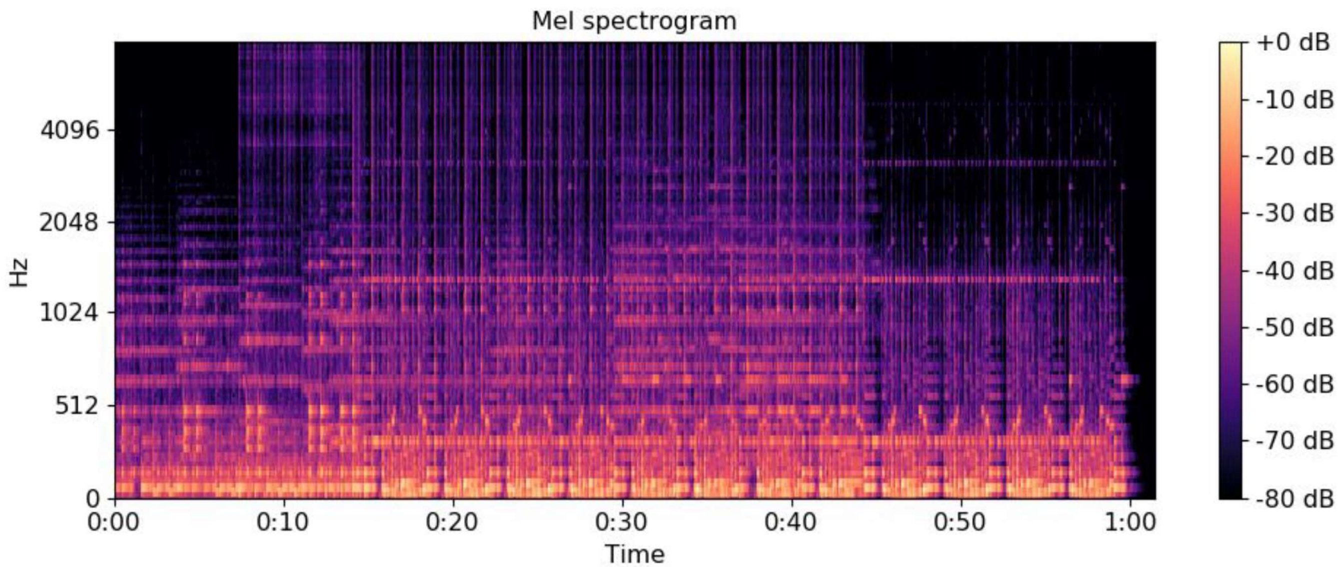
Using satellite imagery, we can automate road + building mapping.



http://openaccess.thecvf.com/content_cvpr_2018_workshops/papers/w4/Zhou_D-LinkNet_LinkNet_With_CVPR_2018_paper.pdf
https://ai.facebook.com/blog/mapping-roads-through-deep-learning-and-weakly-supervised-training/
https://github.com/matterport/Mask_RCNN

Sound Classification

Spectrograms of sounds can be computed using fourier transforms. The spectrograms can then be treated just like images in the context of sound classification.



https://librosa.github.io/librosa/generated/librosa.feature.melspectrogram.html

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Generative Adversarial Networks (GANs)

GANs

Generative Adversarial Networks, or GANs, are a special kind of algorithms that make two separate networks compete against each other. The first network is called a **generator** and the other a **discriminator**.

Generator

Generates samples that look convincingly real

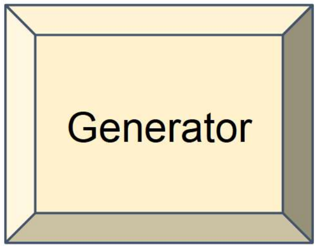
Discriminator

Determines whether a sample is real or generated

https://arxiv.org/pdf/1406.2661.pdf

GANs

This can be thought of as a game between a **counterfeiter** and an **art curator**. The counterfeiter must make fake images that look so real that the curator will falsely identify them as real.



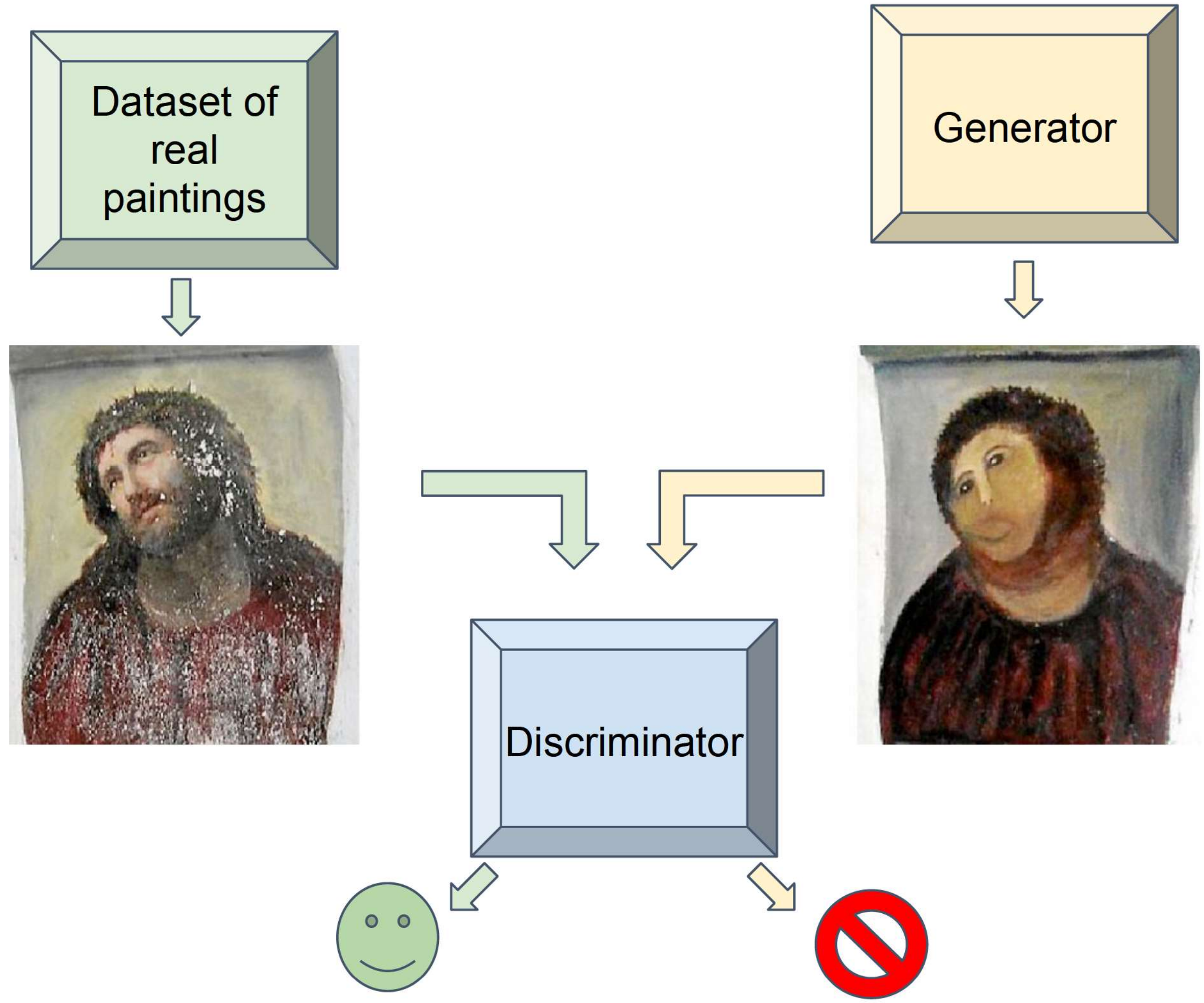
Generates samples that look convincingly real

Determines whether a sample is real or generated

https://arxiv.org/pdf/1406.2661.pdf

GANs

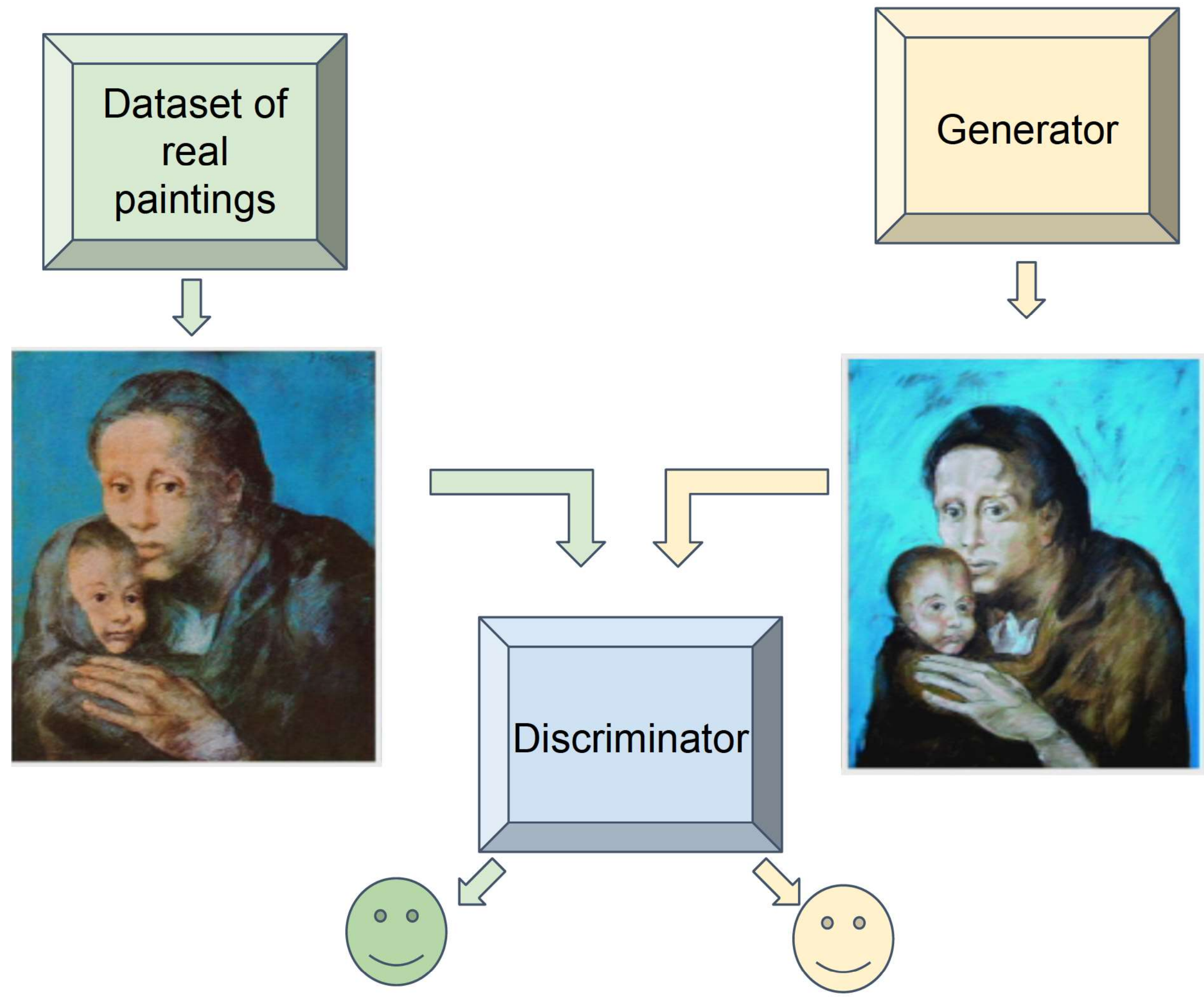
The counterfeiter (generator) attempts to generate real looking images. At first the generator is pretty bad.



https://www.pri.org/stories/2012-08-25/amateur-restoration-botches-jesus-painting-spain

GANs

Eventually, the generator learns to fool the discriminator and can generate convincing images.



https://www.channel4.com/news/art-forgery-beltracchi-wolfgang-ernst-picasso-paraic-obrien

GANs

Mathematically, this can be expressed as a **MinMax** game, where the generator tries to **minimize** the objective function *V* while the discriminator tries to **maximize** it. Both networks are trained successively.

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

Where:

$D(x)$ is a neural network that predicts how confident it is that the input image $\boldsymbol{x}$ is real. The output of *D* can be interpreted as “the **probability** that the sample is real”.

$G(z)$ is a neural network that generates an image given a noise signal *z*

https://arxiv.org/pdf/1406.2661.pdf

GANs

When training the **generator**, we want to **minimize** the term in blue, i.e. we want to maximize the error that *D* will make on a generated image *G(z)*.

$$\boxed{\min_G} \max_D V(D, G) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \boxed{\mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]}.$$

$D(x)$ is a neural network that predicts how confident it is that the input image $\boldsymbol{x}$ is real. The output of *D* can be interpreted as “the **probability** that the sample is real”.

$G(z)$ is a neural network that generates an image given a noise signal *z*

https://arxiv.org/pdf/1406.2661.pdf

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GANs

When training the **discriminator**, we want to **maximize** the terms in red, i.e. we want to minimize the error that *D* will make on a generated image *G(z).*

$$\min_G \boxed{\max_D} V(D,G) = \boxed{\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})]} + \boxed{\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1-D(G(\boldsymbol{z})))]}.$$

$D(x)$ is a neural network that predicts how confident it is that the input image $\boldsymbol{x}$ is real. The output of *D* can be interpreted as "the **probability** that the sample is real".

$G(z)$ is a neural network that generates an image given a noise signal *z*

https://arxiv.org/pdf/1406.2661.pdf

GANs

Notice that the discriminator and generator are trained **iteratively**.

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

Maximize

end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

Minimize

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

https://arxiv.org/pdf/1406.2661.pdf

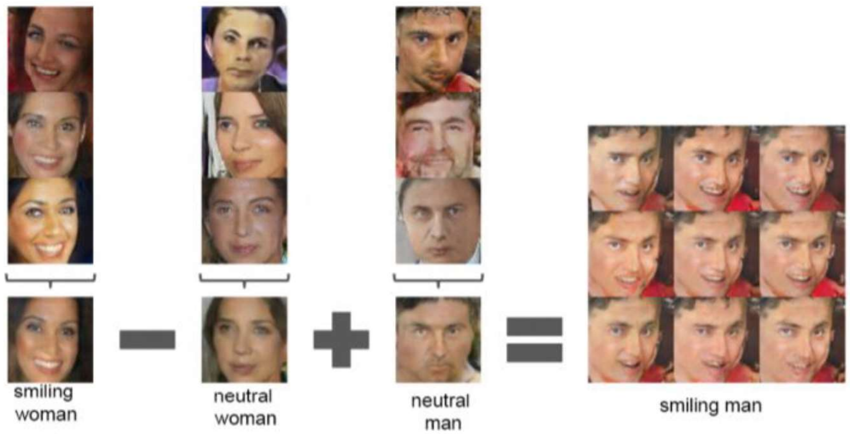
GANs

In the original paper, both digits and faces were generated by the netweork and look convincingly real. The yellow boxes show the closest match to its generated neighbors in the training dataset.

https://arxiv.org/pdf/1406.2661.pdf

DCGAN

In a follow up paper, CNNs are used to generate the images. Transposed convolutions are used for upsampling.



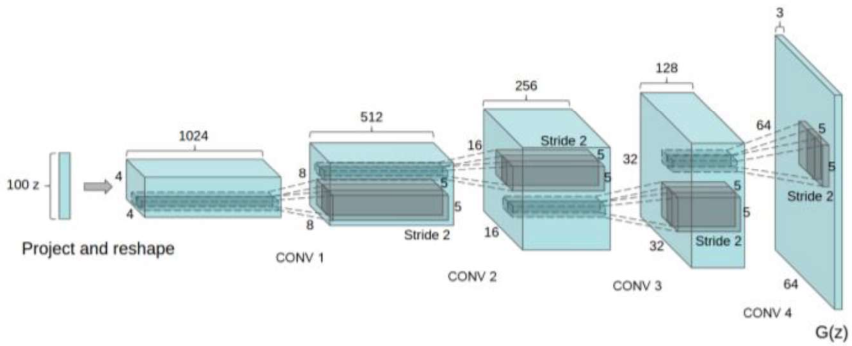


Figure 1: DCGAN generator used for LSUN scene modeling. A 100 dimensional uniform distribution Z is projected to a small spatial extent convolutional representation with many feature maps. A series of four fractionally-strided convolutions (in some recent papers, these are wrongly called deconvolutions) then convert this high level representation into a 64×64 pixel image. Notably, no fully connected or pooling layers are used.

https://arxiv.org/pdf/1511.06434.pdf

Image Synthesis

We can teach networks to generate realistic images that have never been seen before by the network. Which face is fake?

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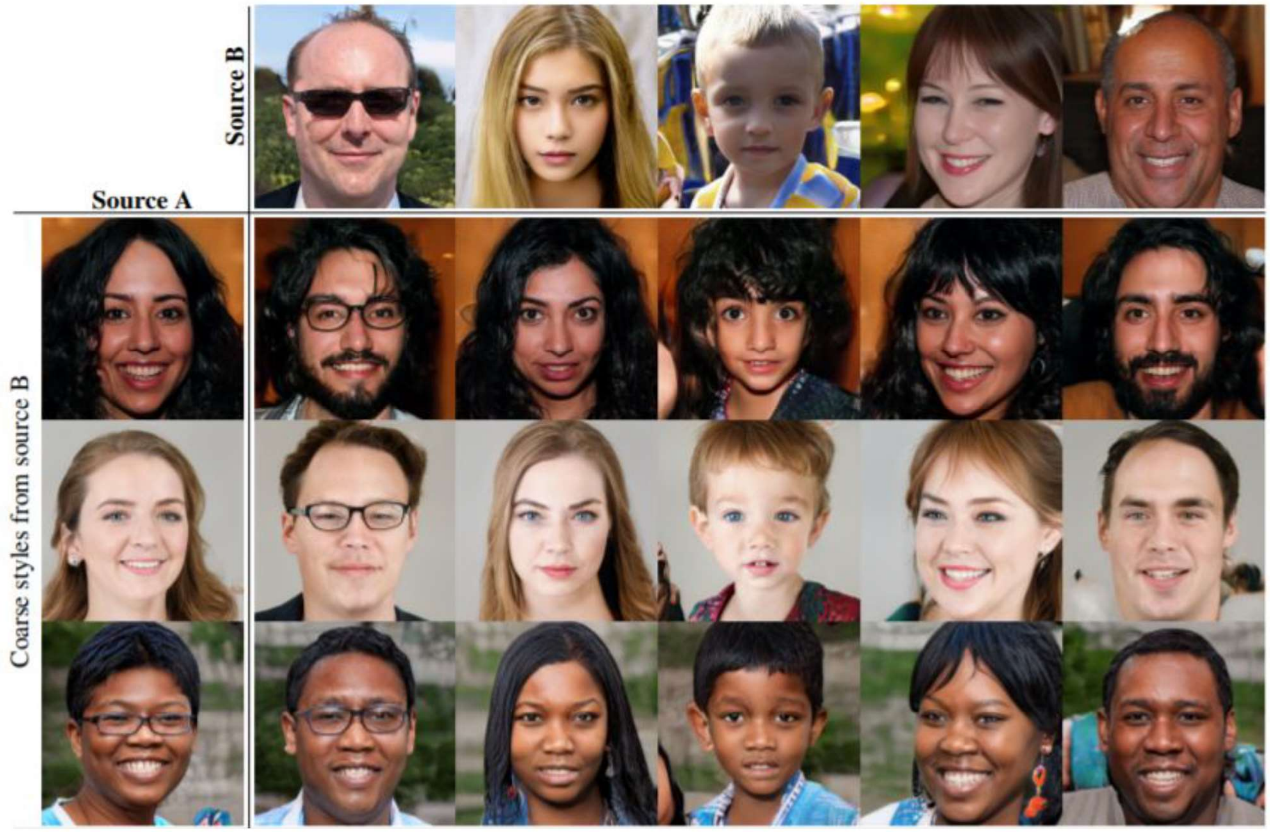
Style Transfer



https://arxiv.org/pdf/1812.04948.pdf

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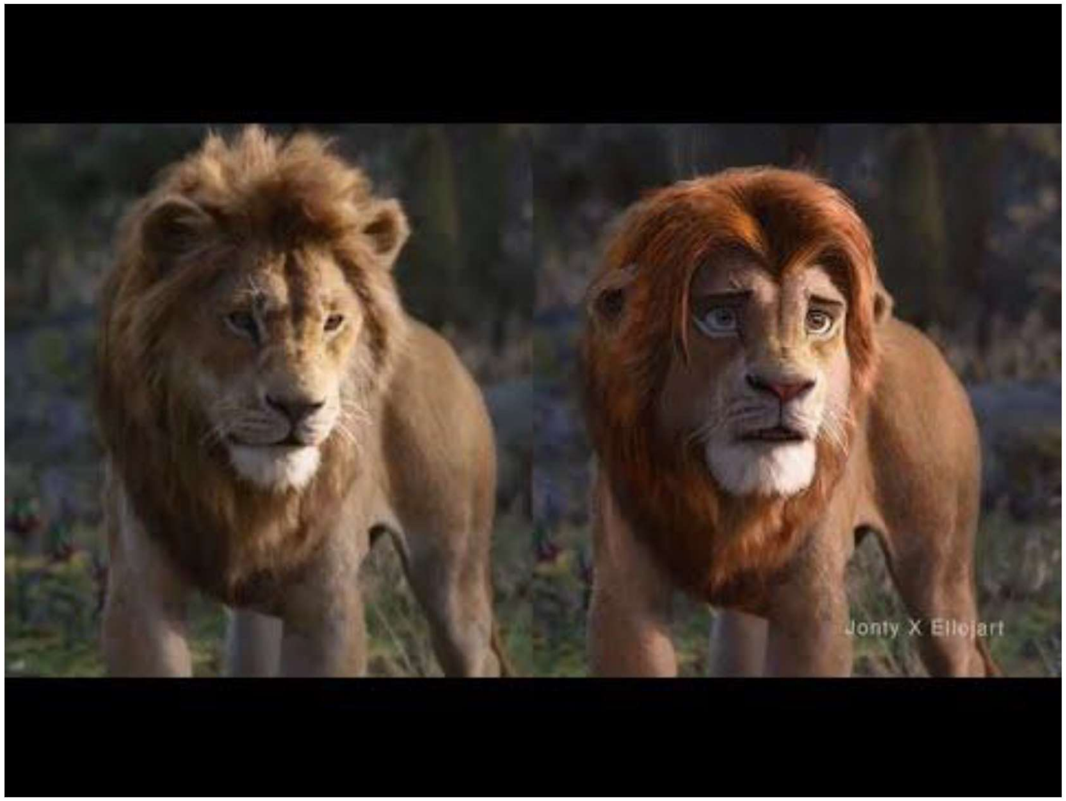
Style Transfer



CycleGAN

CycleGan introduced the concept of **cycle-consistency** loss to their GANs. This allowed training generators that would unpaired images from domain X to domain Y.

Aging Generator

"*De-Aging*" Generator

$$x \to G(x) \to F(G(x)) \approx x$$

$$\begin{aligned}\mathcal{L}_{\text{cyc}}(G, F) = \;& \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] \\ & + \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1].\end{aligned}$$

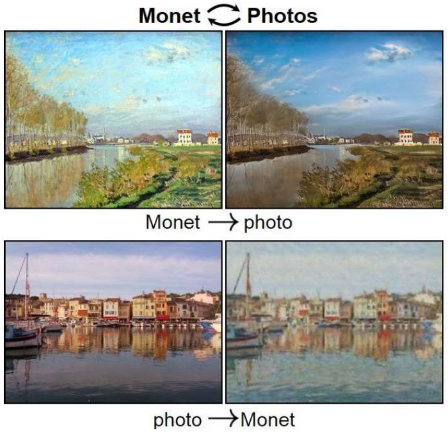
https://arxiv.org/pdf/1703.10593.pdf

https://junyanz.github.io/CycleGAN/

CycleGAN

This allows us to map between arbitrary domains with realistic results.

$$horse \rightarrow zebra$$



https://junyanz.github.io/CycleGAN/
https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix

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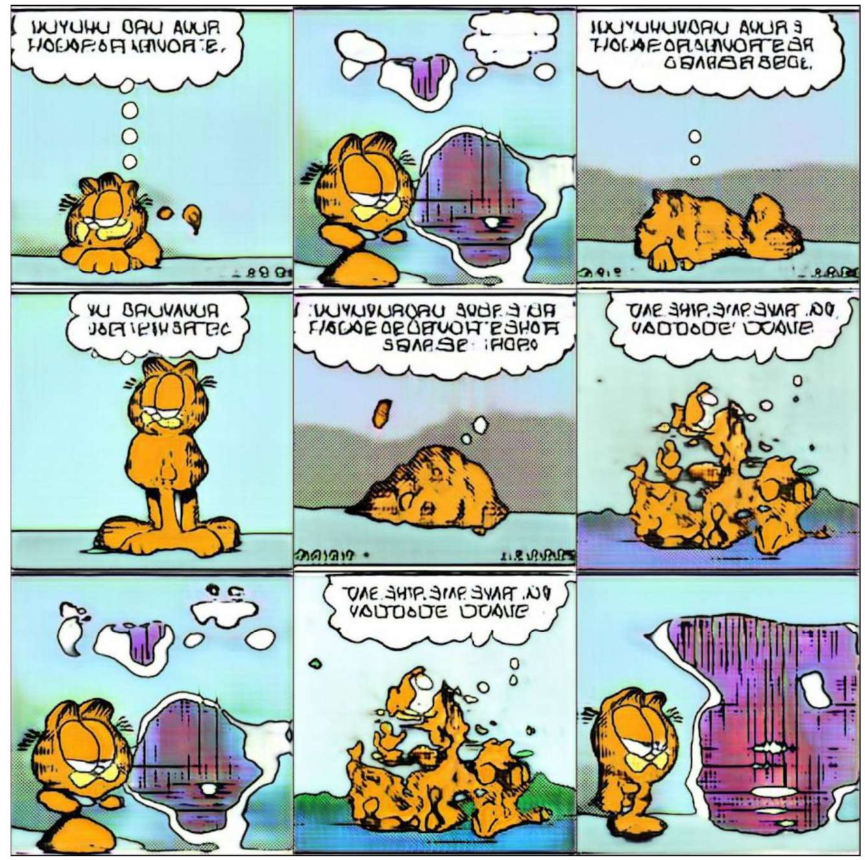
GANfield

You can use GANs to generate convincingly new and original Garfield content



https://vdalv.github.io/2018/12/04/ganfield.html
https://en.wikipedia.org/wiki/File:Garfield_the_Cat.svg

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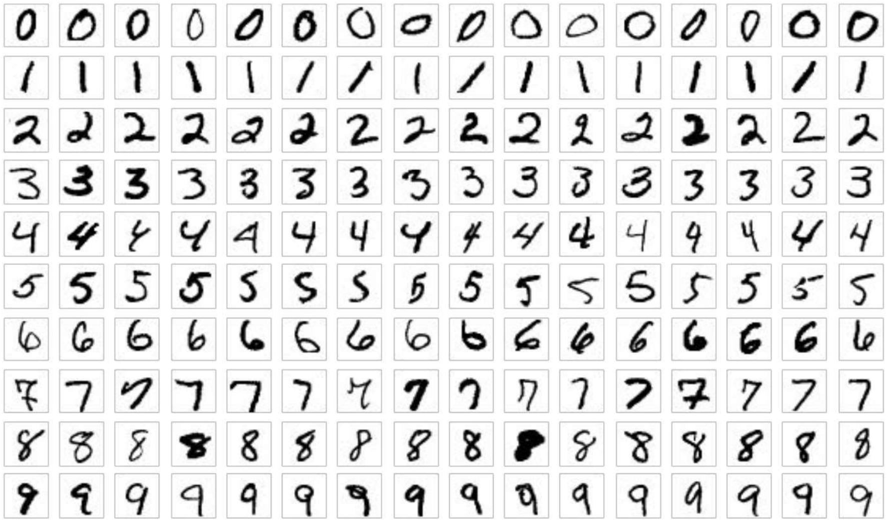
CNN Datasets

MNIST

- 60 000 handwritten digits
- Grayscale images, 28 x 28 resolution
- Easy to train



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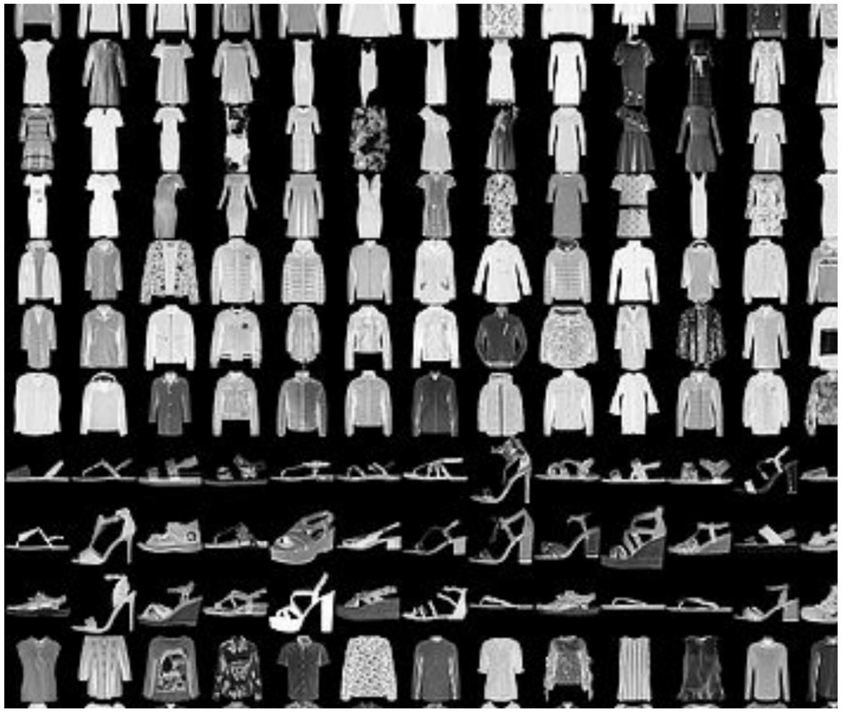
Fashion-MNIST

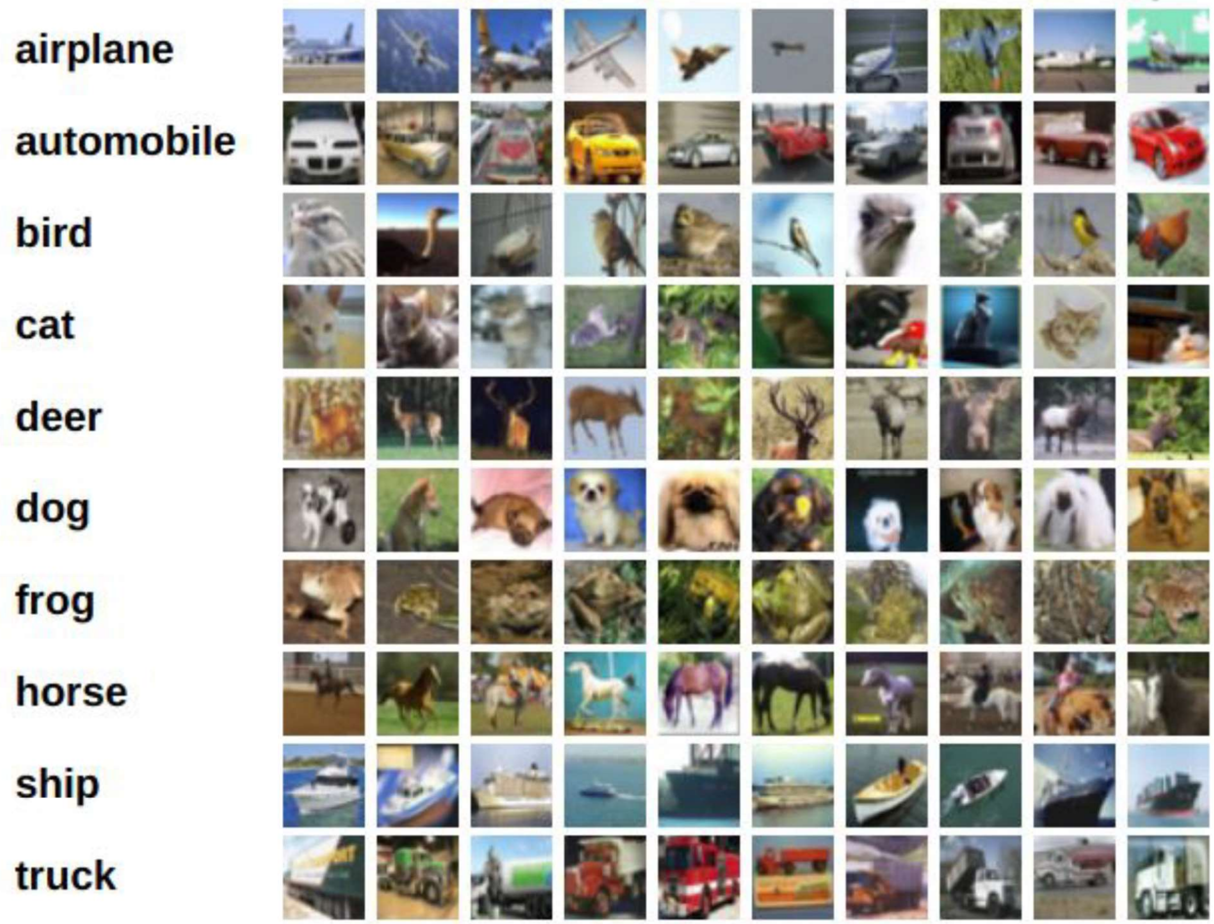
- Like MNIST, but more fashionable (and a little harder)
- 10 categories (sneaker, shirt, boot, etc.)
- Grayscale images
- "If it doesn't work on MNIST, it won't work at all", they said. "Well, if it does work on MNIST, it may still fail on others."



https://github.com/zalandoresearch/fashion-mnist

CIFAR-10

- 60 000 RGB images
- 32x32 (low resolution)
- 10 classes with 6000 images per class



https://www.cs.toronto.edu/~kriz/cifar.html

CIFAR-100

- 60 000 RGB images
- 32x32 (low resolution)
- 100 classes with 600 images

Classes
beaver, dolphin, otter, seal, whale
aquarium fish, flatfish, ray, shark, trout
orchids, poppies, roses, sunflowers, tulips
bottles, bowls, cans, cups, plates
apples, mushrooms, oranges, pears, sweet peppers
clock, computer keyboard, lamp, telephone, television
bed, chair, couch, table, wardrobe
bee, beetle, butterfly, caterpillar, cockroach
bear, leopard, lion, tiger, wolf
bridge, castle, house, road, skyscraper
cloud, forest, mountain, plain, sea
camel, cattle, chimpanzee, elephant, kangaroo
fox, porcupine, possum, raccoon, skunk
crab, lobster, snail, spider, worm
baby, boy, girl, man, woman
crocodile, dinosaur, lizard, snake, turtle
hamster, mouse, rabbit, shrew, squirrel
maple, oak, palm, pine, willow
bicycle, bus, motorcycle, pickup truck, train
lawn-mower, rocket, streetcar, tank, tractor

https://www.cs.toronto.edu/~kriz/cifar.html

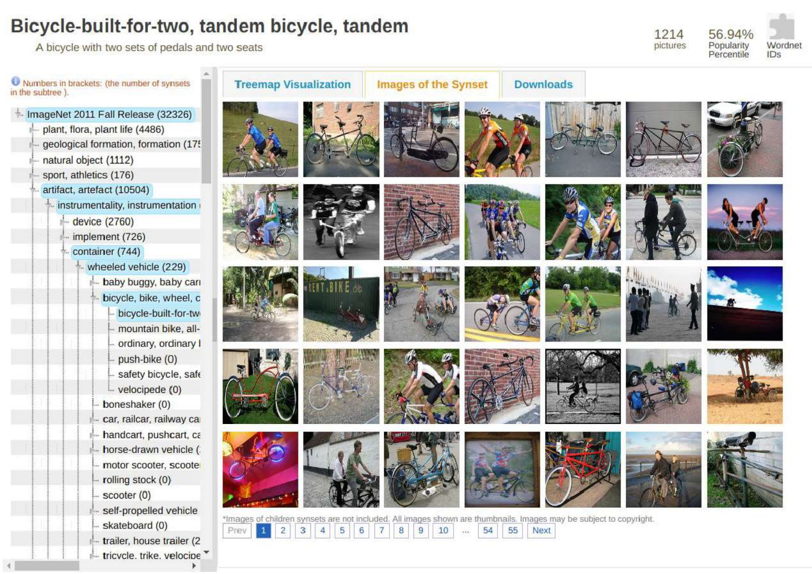
SVHN

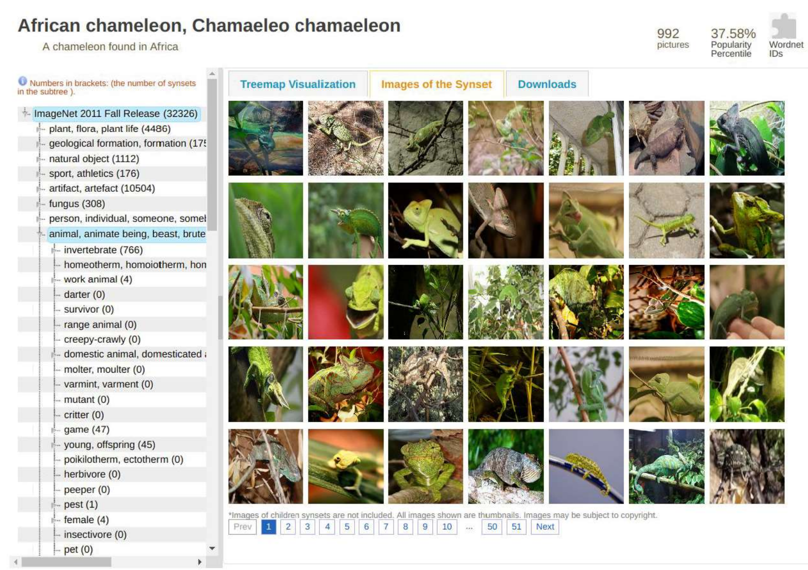
- Street View House Number dataset
- Like MNIST - but harder
- Bounding boxes are provided for each digit
- Approximately 600 000 labelled digits
- Not very high resolution

http://ufldl.stanford.edu/housenumbers/

ImageNet

ImageNet is one of the most widely used datasets in image classification. It has paved the way for many important discoveries in CNN architectures.

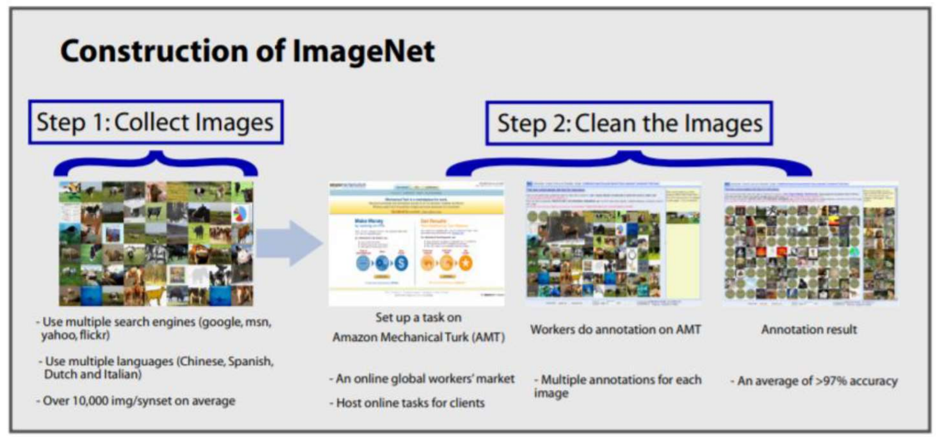




http://imagenet.stanford.edu/

ImageNet

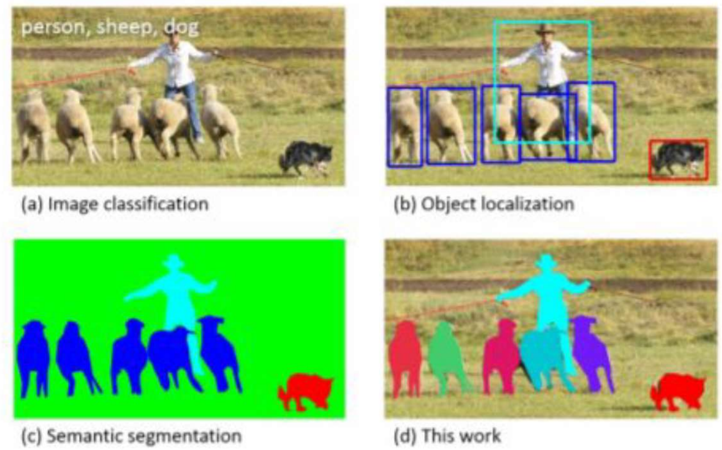
- RGB images with 256x256 resolution
- It consists of 3.2 **million images** manually labelled with thousands of categories.
- ImageNet leveraged crowd-sourcing of data labelling



http://www.image-net.org/papers/ImageNet_VSS2009.pdf
https://qz.com/1034972/the-data-that-changed-the-direction-of-ai-research-and-possibly-the-world/

MS COCO Dataset

- **C**ommon **O**bjects in **CO**ntext
- Instance Segmentation dataset
- **328 000** images with 2.5 million labeled instances and 91 common object categories



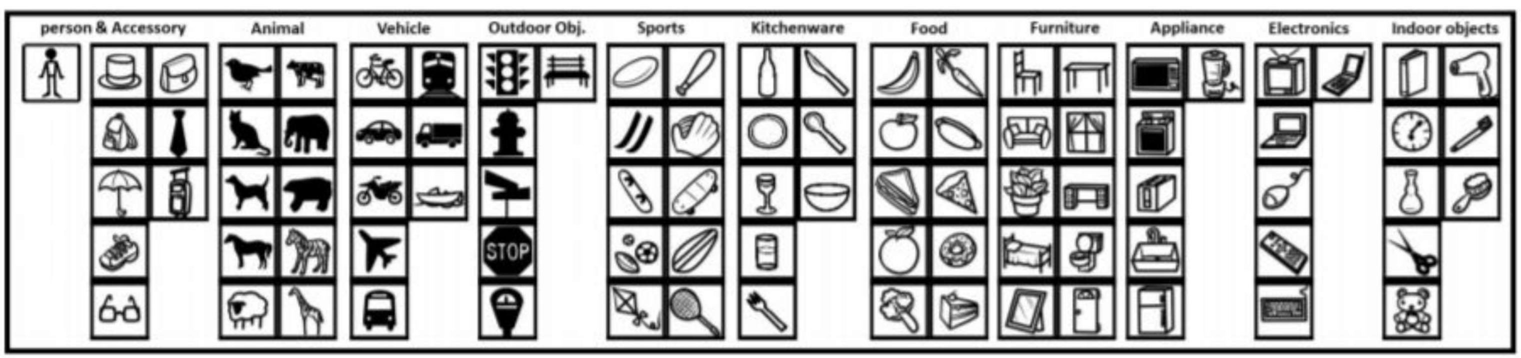
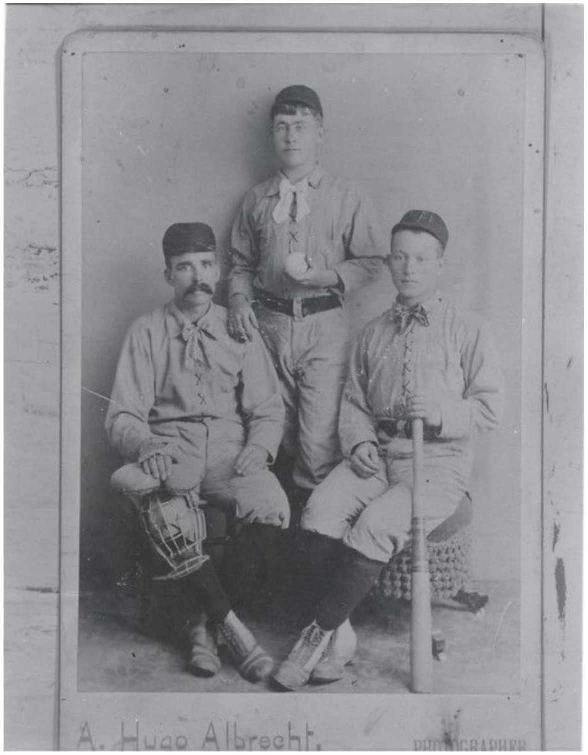


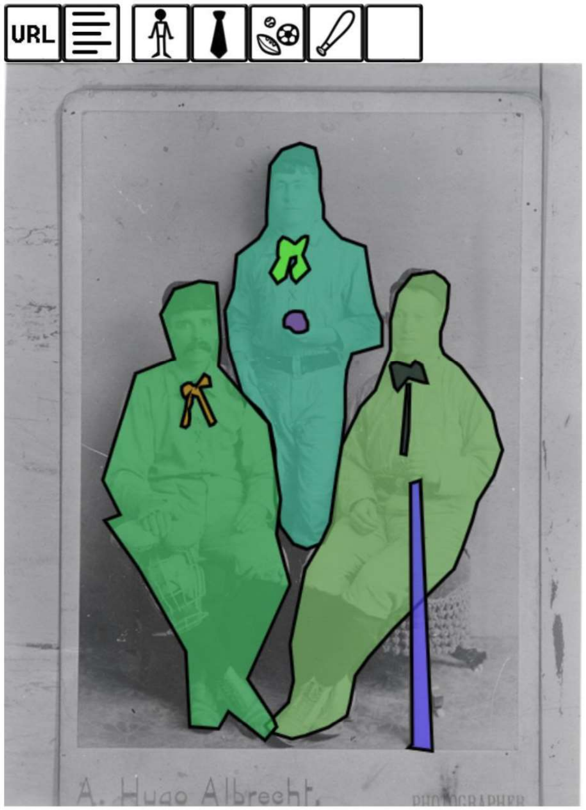
Fig. 11: Icons of 91 categories in the MS COCO dataset grouped by 11 super-categories. We use these icons in our annotation pipeline to help workers quickly reference the indicated object category.

http://cocodataset.org/#home
https://arxiv.org/pdf/1405.0312.pdf

MS COCO Dataset

- Rich level of detail in instance segmentation





http://cocodataset.org/#explore?id=449921
https://farm9.staticflickr.com/8145/7595393302_58cf5044f8_z.jpg

MS COCO Dataset

- **C**ommon **O**bjects in **CO**ntext
- Keypoint detection dataset
- Over 150,000 people and 1.7 million labeled keypoints

http://cocodataset.org/#keypoints-2019

Collecting your own dataset

- Look for similar datasets first
- Understand the kind of labels you need and how you want to represent them
- Labelling can be expensive and inaccurate
- Synthetic data (simulators, GANs, etc.) can work well to test ideas - it can also fail to generalize
- Be sure to have a robust and well guarded test set
- Always challenge the validity of your data

https://medium.com/s/story/no-happy-little-accidents-8663540763f8

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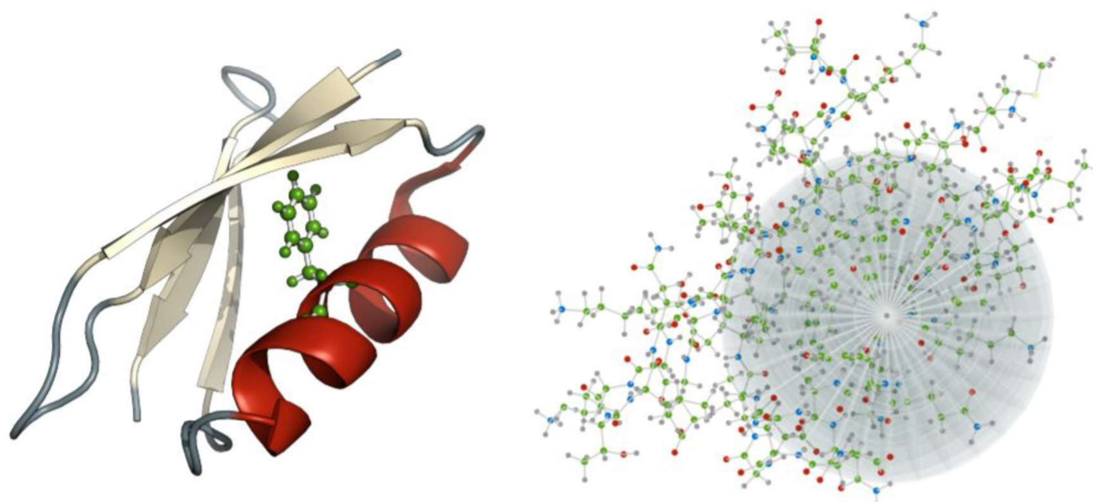
Questions?

Molecular Properties

Spherical CNNs (an extension of CNNs) have shown lots of promise in predictions of properties in molecular and quantum chemistry.



https://papers.nips.cc/paper/6935-spherical-convolutions-and-their-application-in-molecular-modelling.pdf