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Deep Learning in Computer Vision

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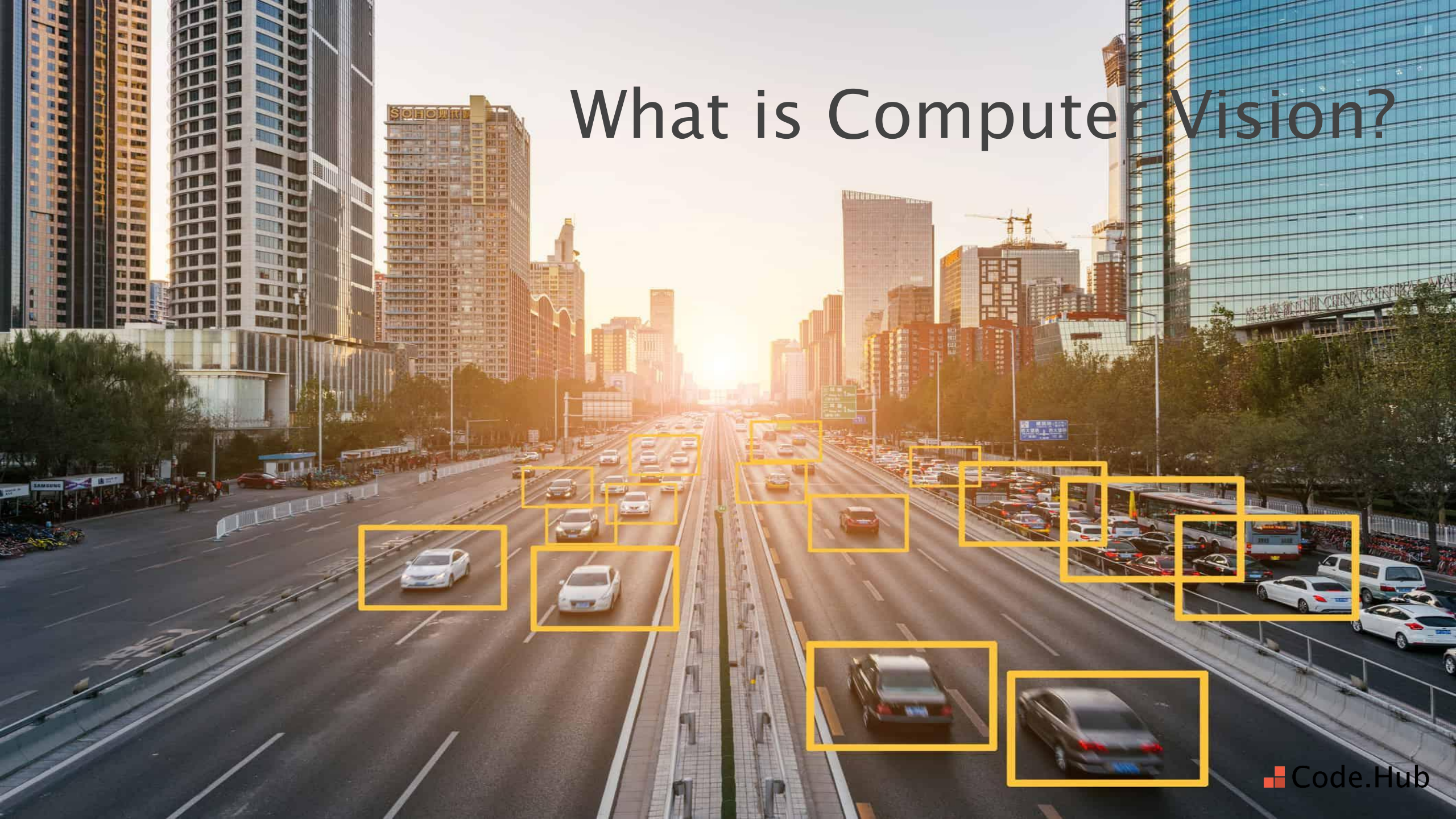
Contents

- **What we'll cover**:
  - intro to Computer Vision
  - Convolutional Neural Networks
  - Interpretability in visual models
- **Prerequisites**:
  - basic understanding of Machine Learning and Neural Networks

What is Computer Vision?



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What is Computer Vision?

Computer Vision is a field of research aiming at developing human-like vision capabilities for computers.

high-level understanding of images and video

Most common tasks

- **Classification**

  determine what does the image show

  (assumes that the image has a single interpretation)

- **Segmentation**

  divide the image into segments according to its content

- **Object Detection**

  detect the different objects inside the image

Note: all of the above are supervised learning tasks

Image Classification

identifies what the image is showing

Image Segmentation

identifies the area of the image that is a “road”

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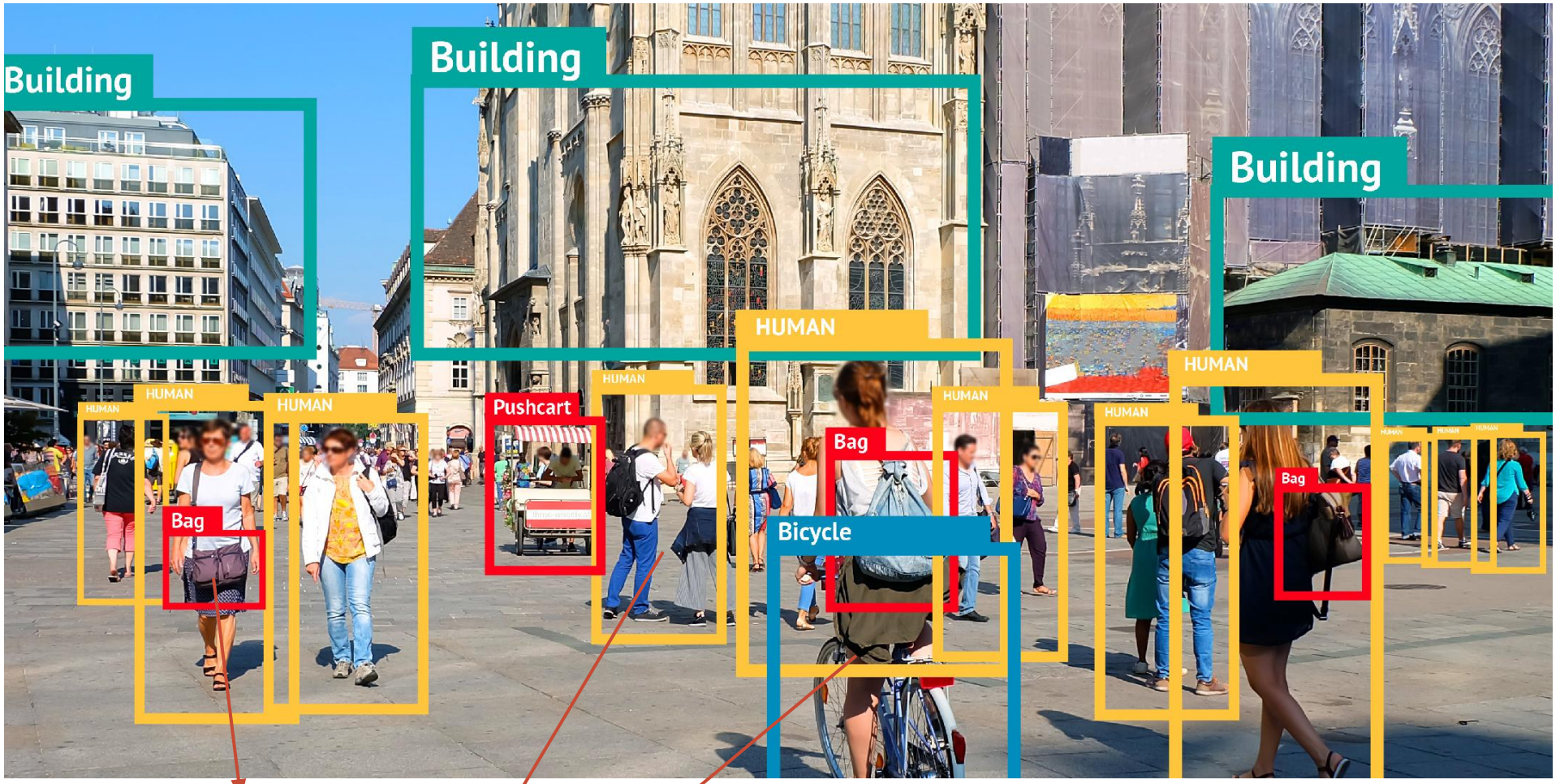
Object Detection



detects the objects in the image

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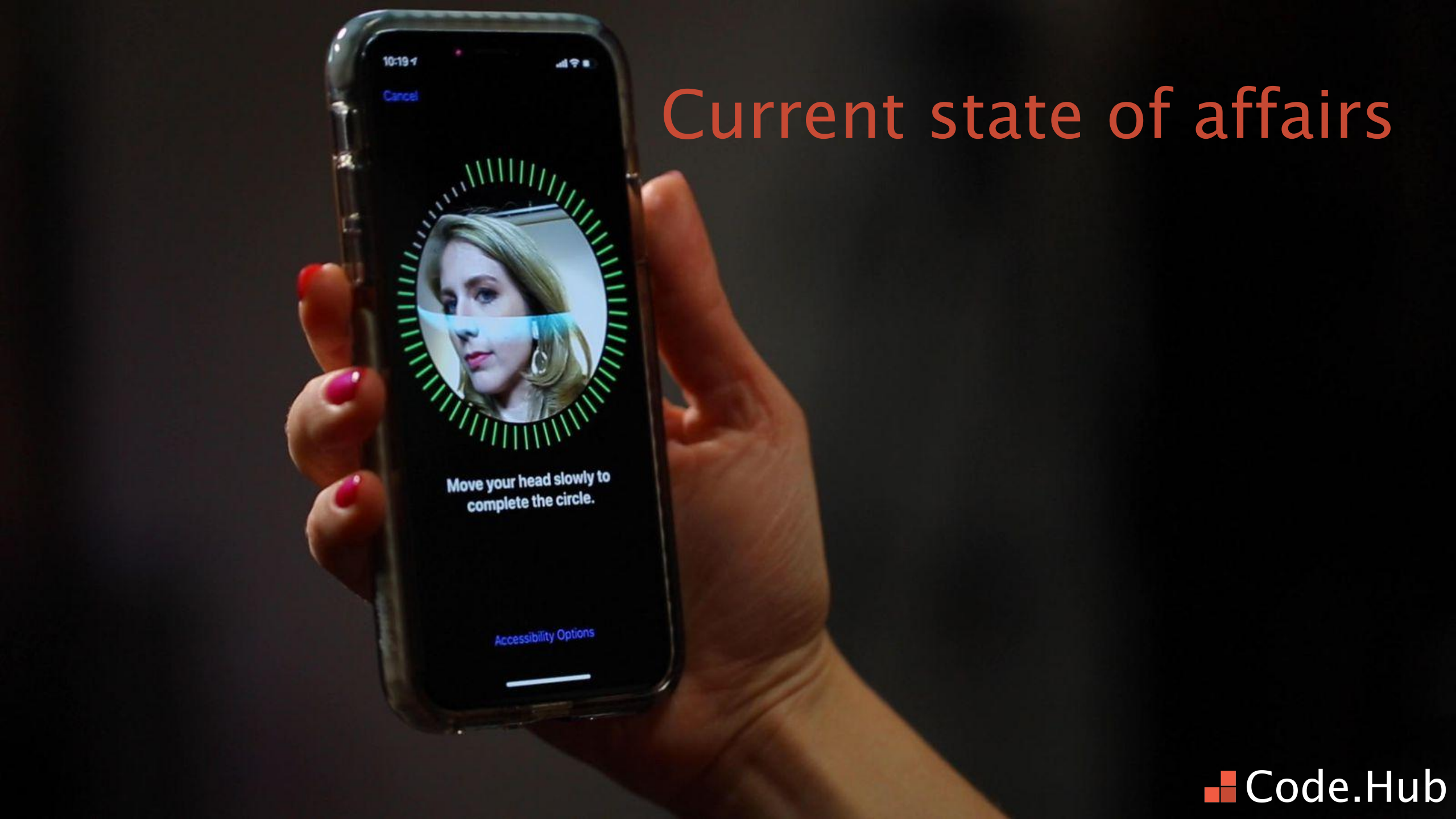
Current state of affairs



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Current state of affairs

photos.google.com/search/cat

cat




Τρί, 30 Ιουλ

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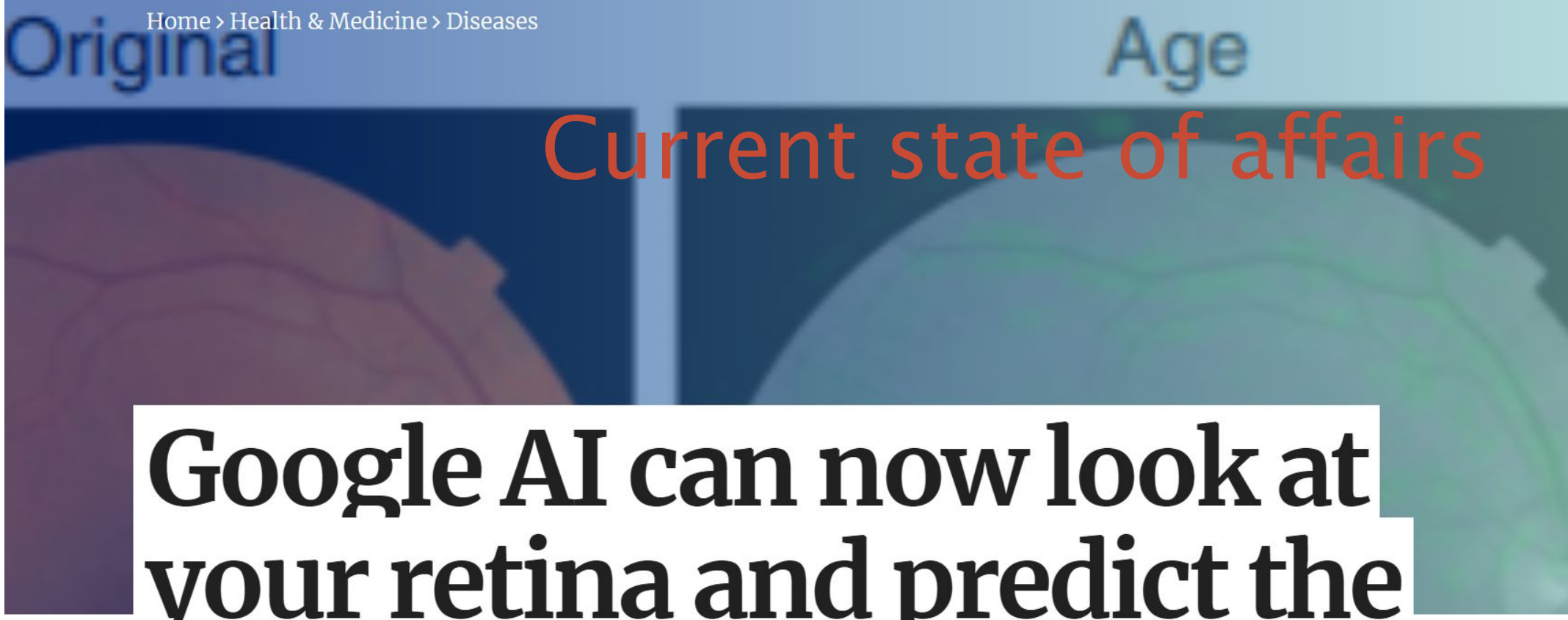


Current state of affairs

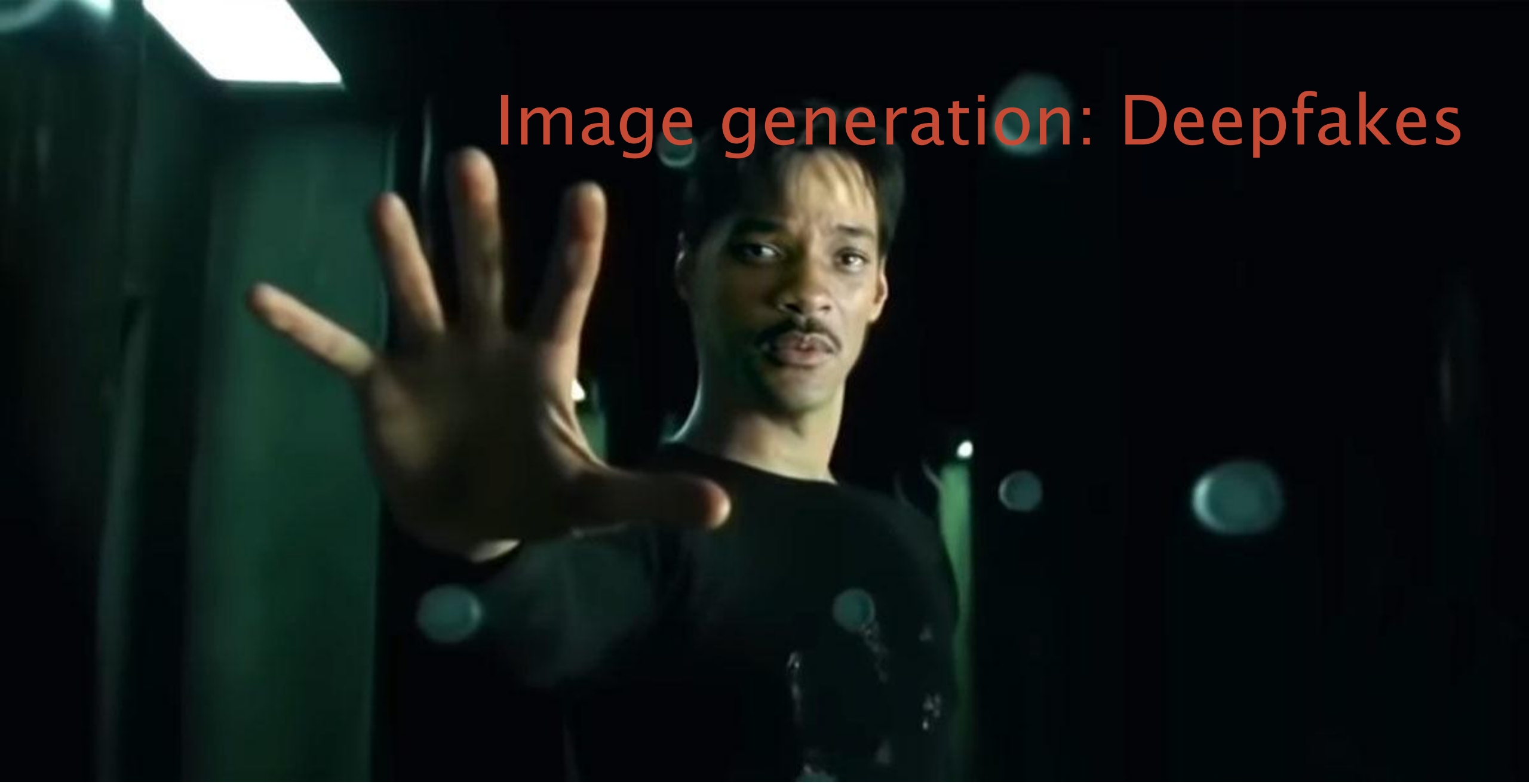
Google AI can now look at your retina and predict the risk of heart disease

After analyzing data from over a quarter million patients, the neural network can predict the patient's age (within a 4-year range), gender, smoking status, blood pressure, body mass index, and risk of cardiovascular disease.

by **Francesca Schiopca** — February 20, 2018 - Updated on February 21, 2018 in **Diseases**, **Science**

Current state of affairs

Image generation: Deepfakes



Teddy bears swimming at the Olympics 400m Butterfly event.

A blue jay standing on a large basket of rainbow macarons.

An art gallery displaying Monet paintings. The art gallery is flooded. Robots are going around the art gallery using paddle boards.

A transparent sculpture of a duck made out of glass. The sculpture is in front of a painting of a landscape.

Imagen

DALL-E

Adobe Photoshop: Generative Fill

Challenges in image recognition

What makes a cat, a cat?

- its tail?
- its paws?
- its ears?
- its eyes?
- its face?

Challenges in image recognition

Challenges:

- Hard to quantify what actually makes a “cat”
- Do all cats look the same?
- Are all cats located in the same position in the image?
- Are all cats located in the same context?

Consequently:

- Hard to approach image-related tasks with traditional programming (e.g. rule-based systems)
- Need for more advanced Machine Learning algorithms.

Behind the hood…

… Machine Learning

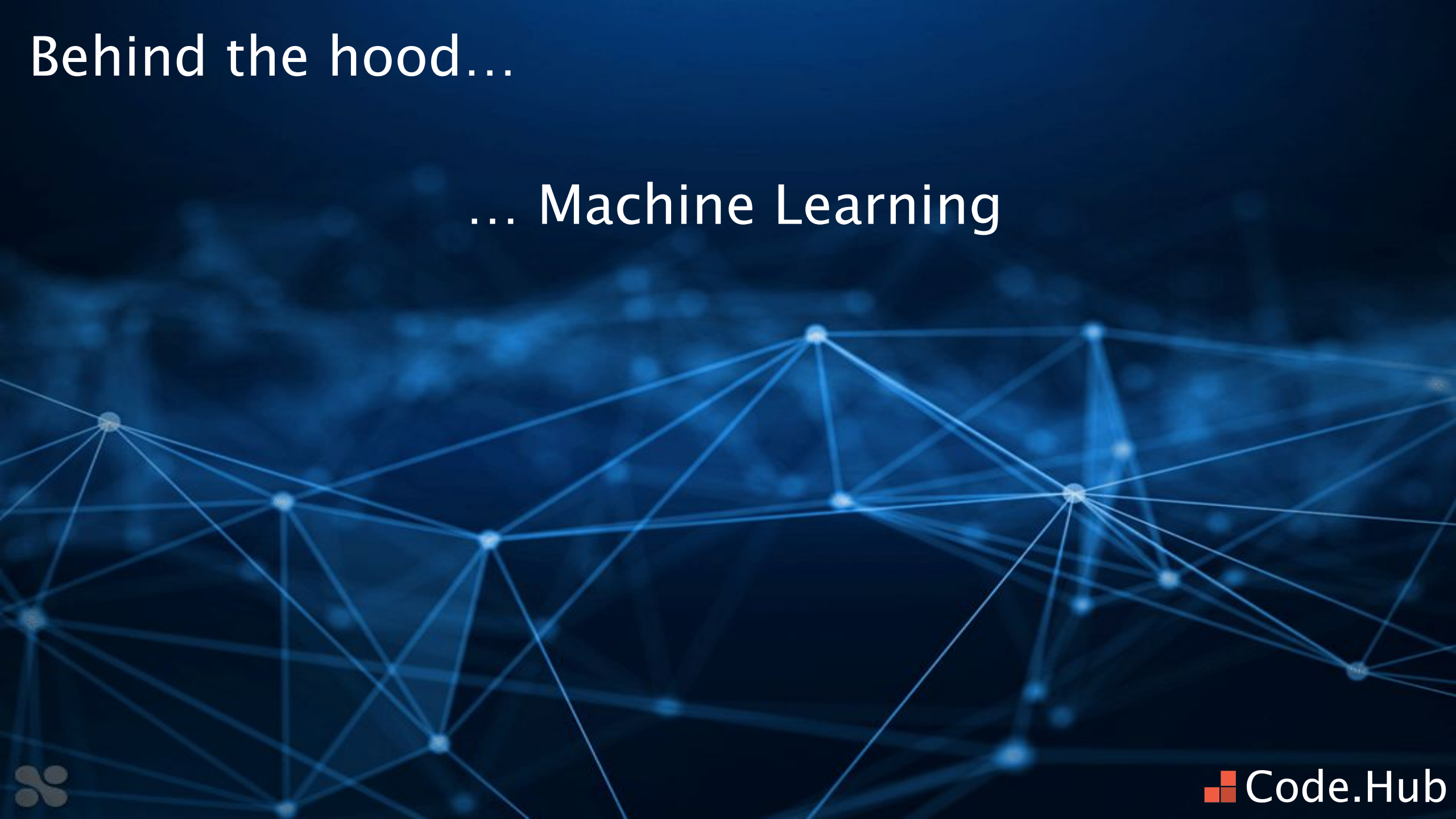


Image classification

Cats vs Dogs

labelled image dataset

ML model

cat cat
cat
cat
dog
dog
dog dog

predict the class labels

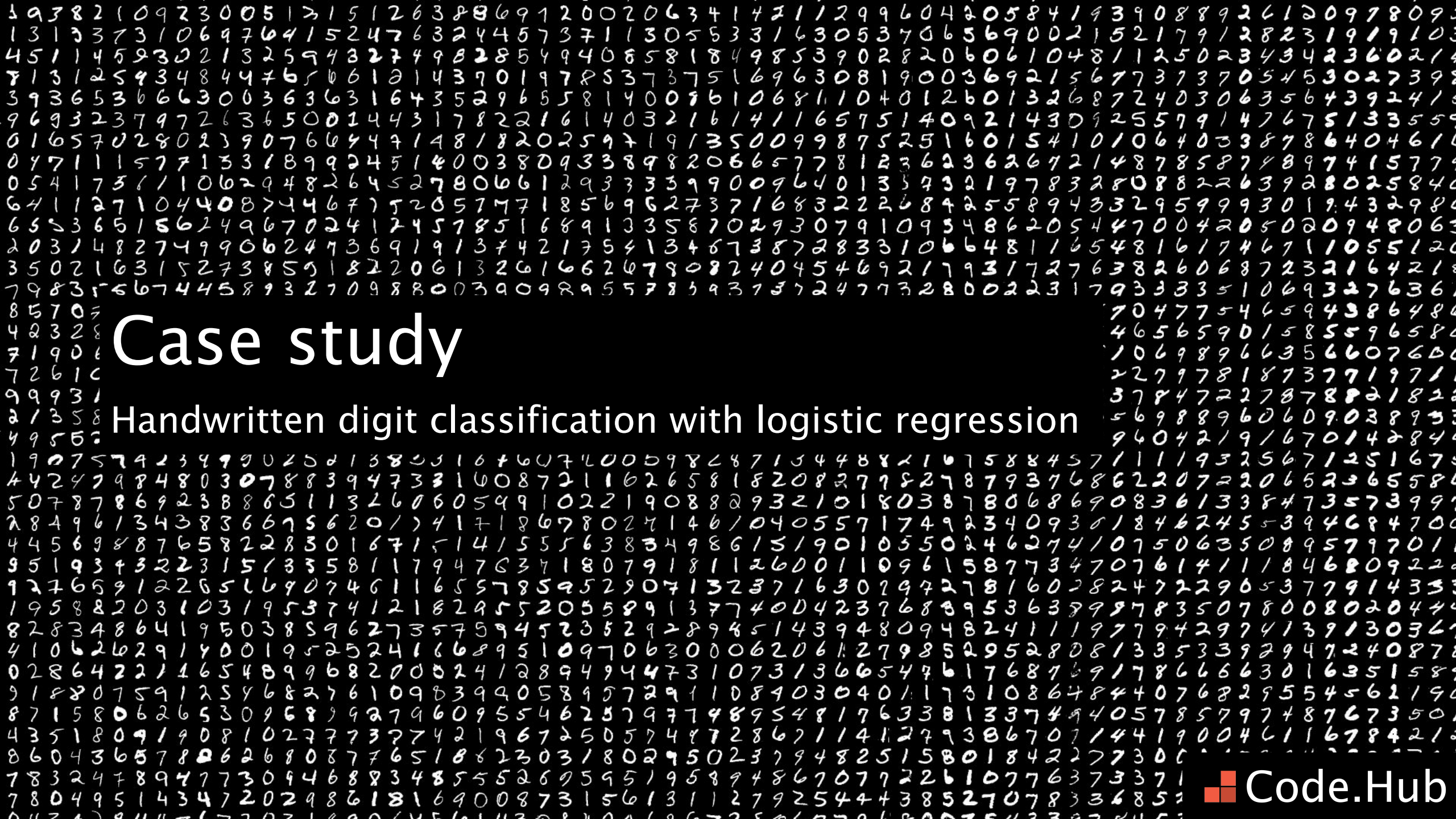
Demystifying ML: caveats

- Key to success: data
  - Require lots of data → the more the better
  - Data needs to be manually annotated → very costly
  - Quality of data is very important → machine bias

- Interpretability is an issue
  - More complex algorithms (e.g. Deep Neural Networks) are considered as “black boxes”.
  - More difficult to assess performance.
  - Industries are slow to adopt.

- In most cases they can’t adapt over time.

- Not easy to insert domain knowledge in ML pipeline.



Case study

Handwritten digit classification with logistic regression

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Deep Learning...

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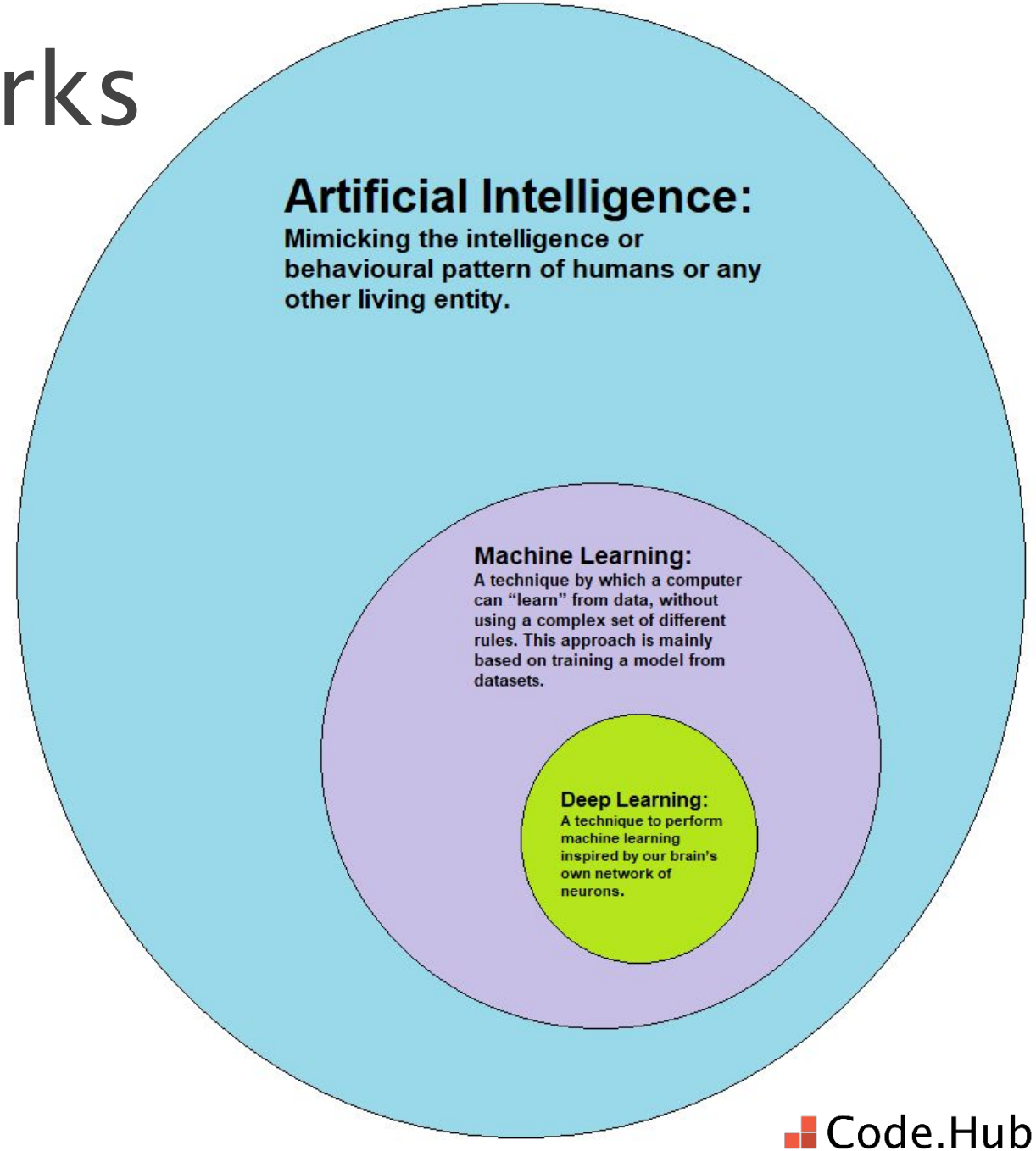
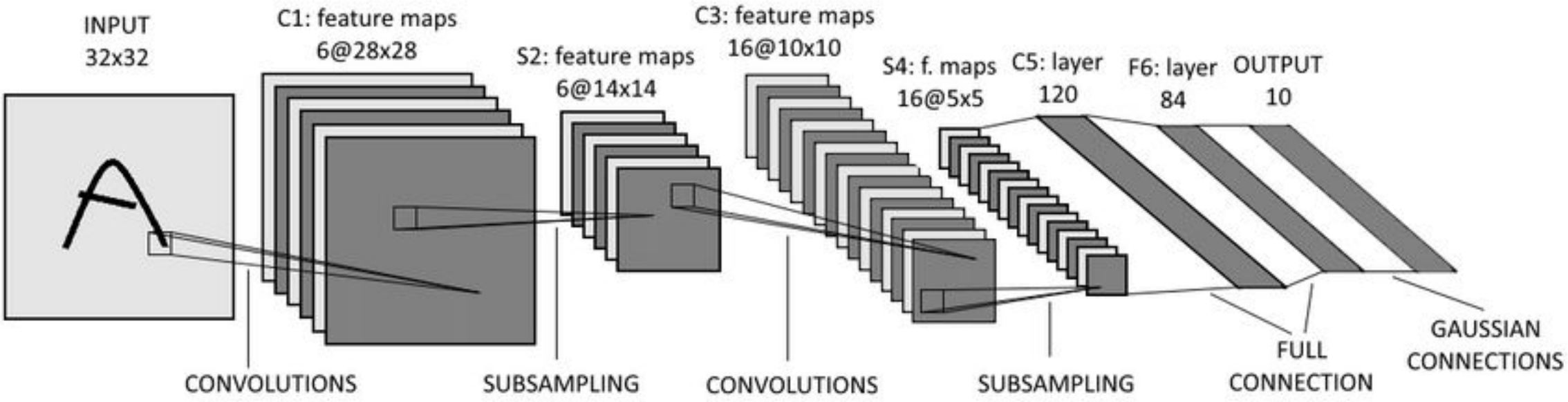
Deep Neural Networks

- Neural Networks with lots of hidden layers.
- Can extract high-level features from the data.



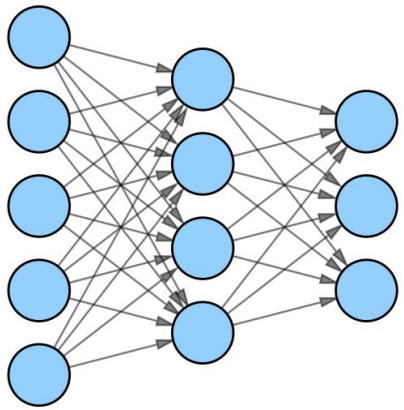
Convolutional Neural Networks

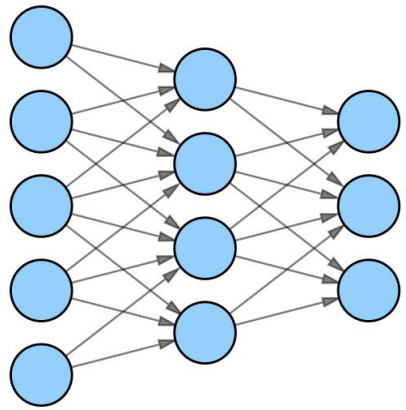


- Input typically represented in 2D (natural orientation of image)
- Exploit concepts like sparse connectivity and weight sharing.
- Work very well with images.
- Extract high-level spatial features.

Sparse Connectivity: Intuition

- Pixels exhibit strong local semantic correlation
- More important to look at local areas rather than global ones
- Local features can be captured by locally (sparsely) connected Neural Networks





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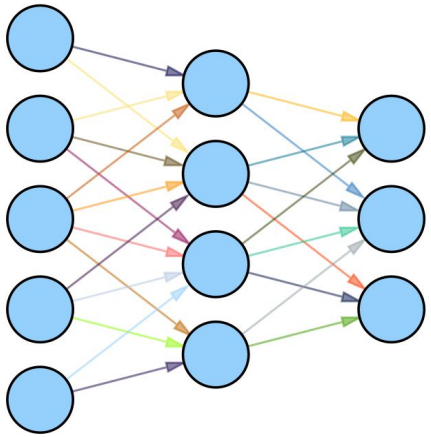
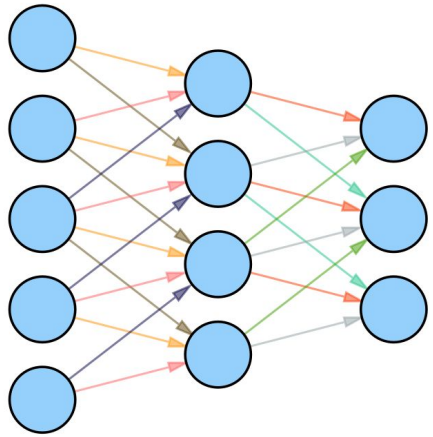
Weight Sharing: Intuition

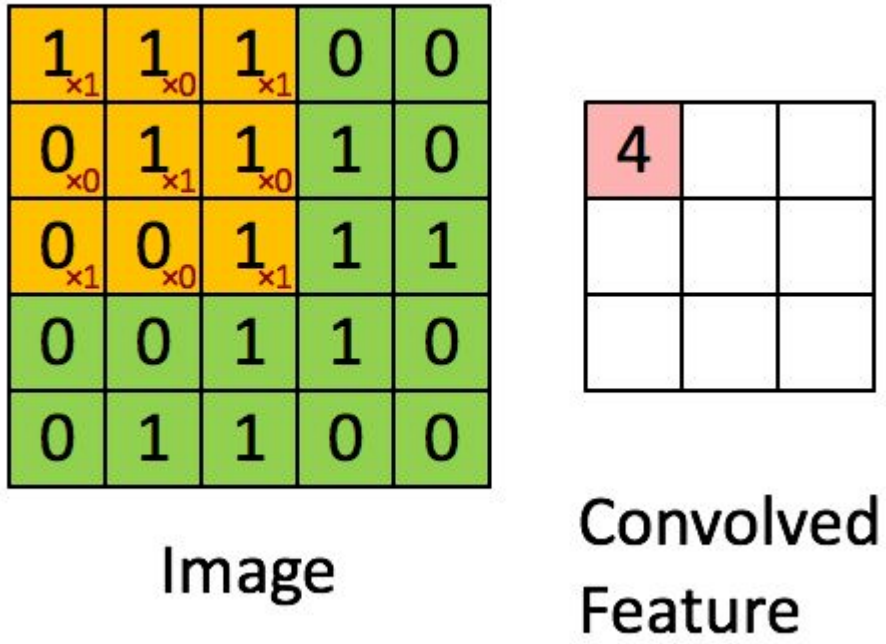
- Objects (e.g. cat's eye) can appear in various locations in an image.
- It makes sense for a Network to be able to detect the same features in any location of the image.
- This is possible through weight sharing.





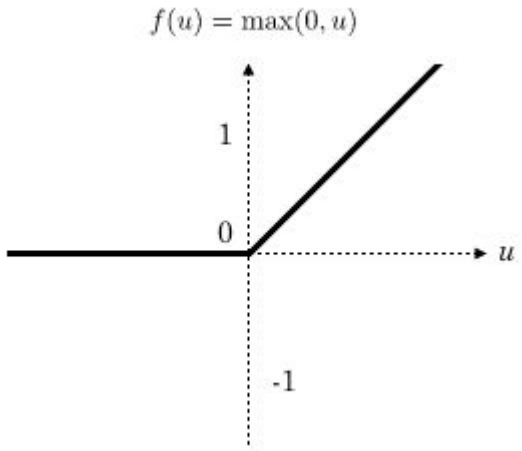
Convolution Layer

- Operation: 2D convolution between input and a kernel
- Parameters:
  - kernel's weights are all trainable
  - bias (tied/untied) [optional]
- Hyperparameters:
  - kernel size (here 3x3)
  - strides (here 1x1)
  - initialization
  - padding (here "valid")
  - etc.



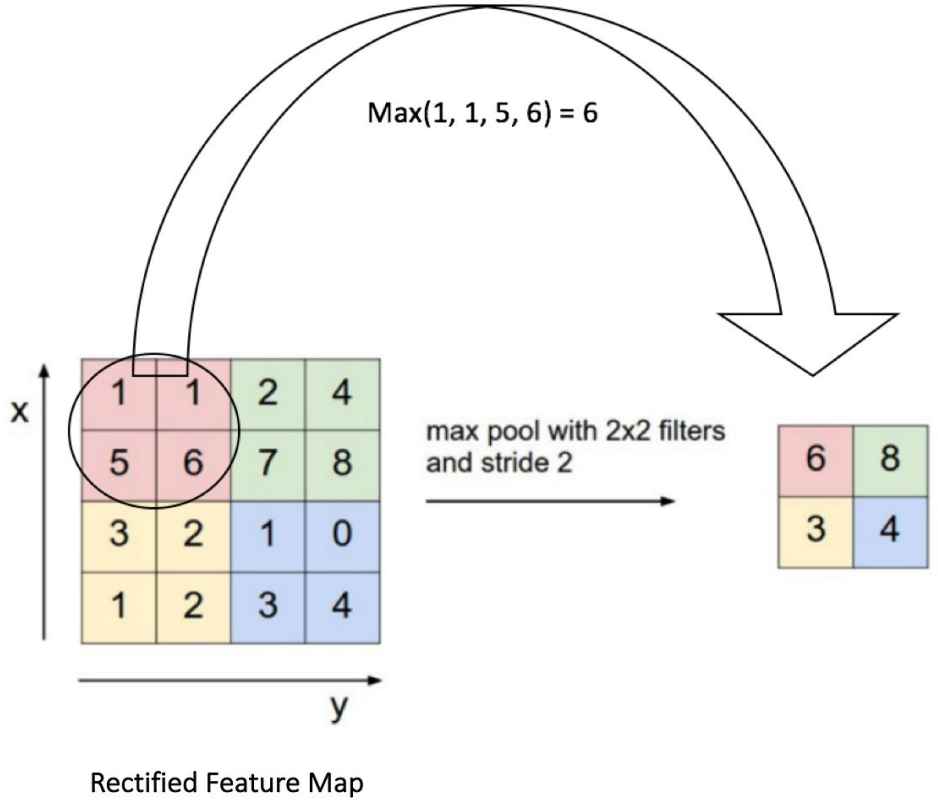
Activation Function

- Convolution layers perform an affine transformation
- A network consisting of only conv layers can't model non-linear functions
- Activation functions are non-linear functions typically applied after linear layers.
- Most popular activation functions:
  - Rectified Linear Unit (ReLU)
  - Other functions from the ReLU family (e.g. PReLU, leaky ReLU, elu, …)
  - Saturating ones (e.g. sigmoid, tanh, …)



Pooling Layer

- Operation: 2D aggregation in input
- Parameters:
  - none
- Hyperparameters:
  - operation (here “max”)
  - size (here 2x2)
  - stride (here 2x2)
  - padding (here “valid”)
- Benefits:
  - reduces the spatial dimensions (less parameters for subsequent layers)
  - makes output invariant to small changes in input
  - makes output equivariant to changes in scale



Case study

Handwritten digit classification with CNN

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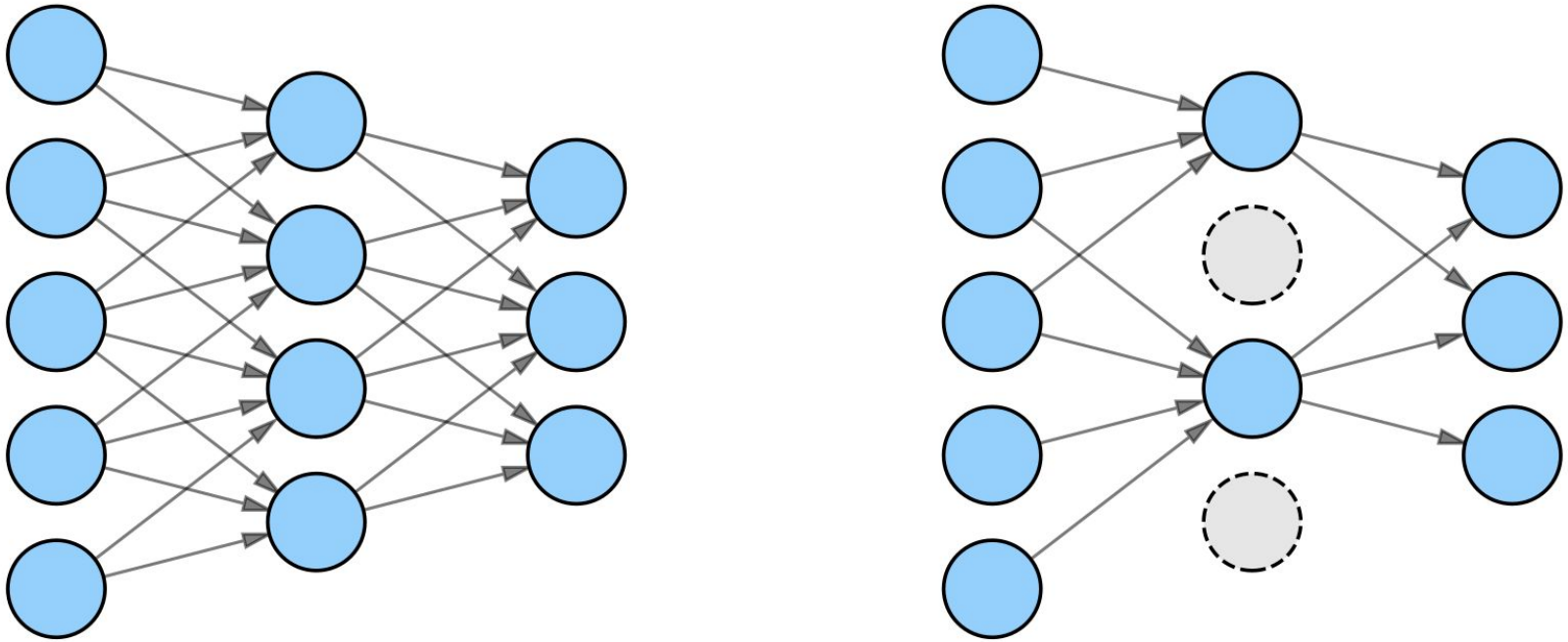
Improvements…

… on the architecture and the training procedure

Dropout

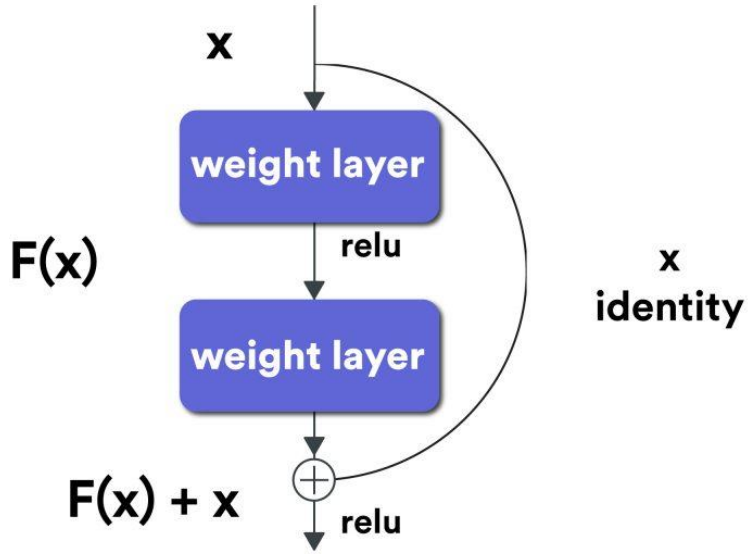
- Most popular regularization technique for Neural Networks
- Works by randomly removing some activations from a layer at each iteration.



- Reduces interdependence between specific neurons.
- In turn, this reduces overfitting.

Skip Connections

- The networks we've seen up till now process the data sequentially
- Idea: disrupt this sequential flow by allowing data (and consequently gradients) to skip certain layers
- Can be implemented two ways: addition (e.g. ResNet), concatenation (e.g. DenseNet)



- Can help with the vanishing/exploding gradient problem of Deep Neural Nets

Batch Normalization

- Technique for increasing training speed and stability, while reducing overfitting.
- Normalizes the input of a layer by batch statistics computed during training.
- Then re-scales and re-shifts the normalized input via two trainable parameters.
- Made way for different intra-layer normalization techniques
  (e.g. layer norm, group norm, instance norm)

Data Augmentation

- More data helps
- Idea: artificially create more images
- If done properly, these will increase the network's performance
- These images will have the same semantic content as the originals, but be regarded as completely different images by the network

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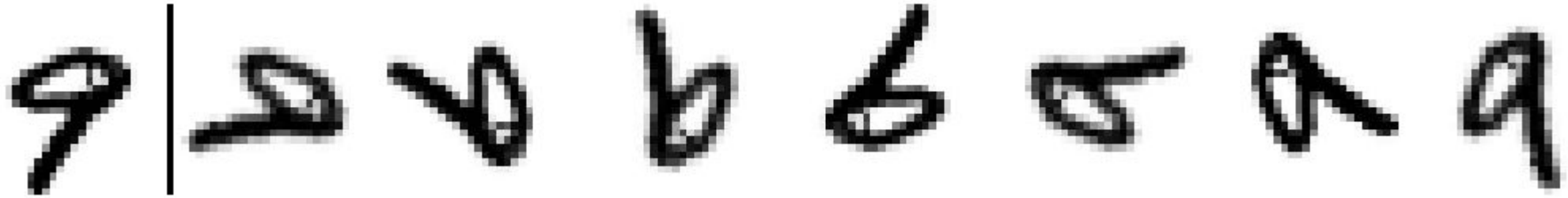
Data Augmentation - caveats

- Too much augmentation can alter the semantic content in an image.



- This can add noise to the dataset and hurt performance.
- Augmentation scheme needs to be selected ad-hoc for each application.

Transfer Learning

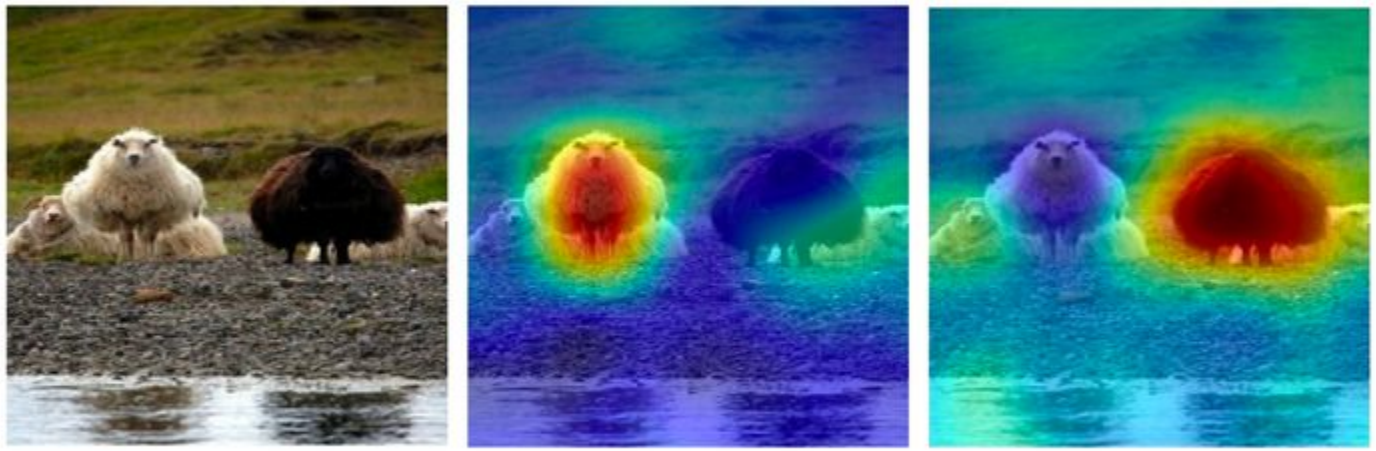
- Models trained on more data perform better
- Some problems don't have enough data
- Idea: train a model on a task that has lots of data (let's call this A, e.g. *ImageNet*) and then use the knowledge it extracted on another dataset that has fewer data (B).
- This is typically done by (sometimes partially) continuing the training of a model trained on A, on data from B.
- This usually leads to a better performance on task B.

Interpretability in visual models

- What is interpretability in Machine Learning?
  - the ability to predict a network's output?
  - the ability to "export" the network's logic into a set of rules?
  - the ability to explain the network's prediction?
- We'll equate interpretability with explainability
  - it is the best we can achieve in practice
  - it is enough for most commercial applications

Saliency map

- What form to explanations come in visual models?



(a) Sheep - 26%, Cow - 17% (b) Importance map of '*sheep*' (c) Importance map of '*cow*'

- Image with the same dimensions as the original which shows the contribution of each pixel towards the final prediction.

Visual Interpretability Techniques

- Hot research topic
- A lot of techniques for explaining the predictions of a CNN
- Most common:

Grad-CAM

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Thank you
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