

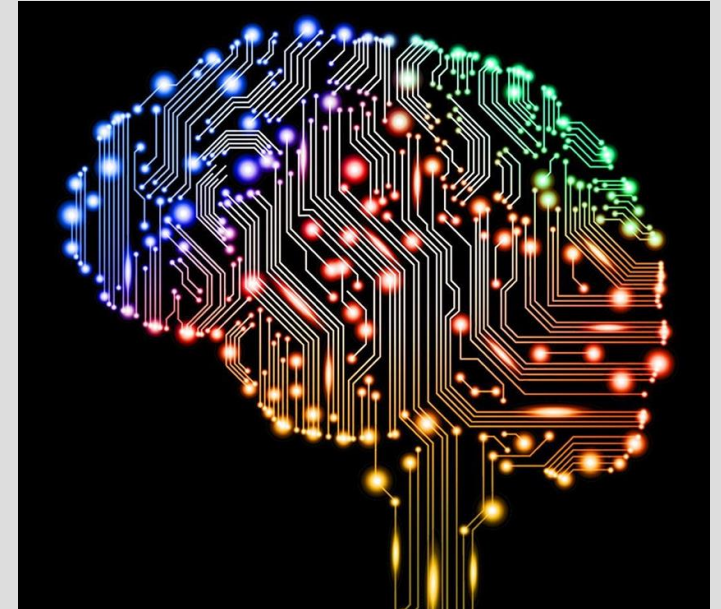
Neural Networks - Deep Learning and Transfer Learning


Topics

- Deep learning
- Convolutional neural networks
- Transfer learning
- Augmentation

Deep Learning

- Biggest thing in “AI” for awhile
- Inspired in part by “deep neural architectures” (human brain)
- Citation crazy





Geoffrey Hinton

Emeritus Prof. Comp Sci, U.Toronto & Engineering Fellow, Google
Verified email at cs.toronto.edu - [Homepage](#)

[machine learning](#) [neural networks](#) [artificial intelligence](#) [cognitive science](#) [computer science](#)

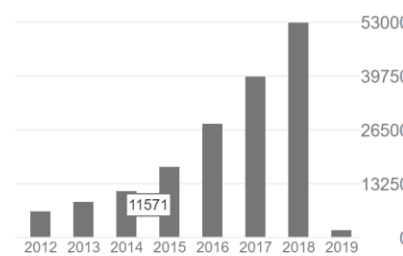
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TITLE	CITED BY	YEAR
Learning internal representations by error-propagation DE Rumelhart, GE Hinton, RJ Williams Parallel Distributed Processing: Explorations in the Microstructure of ...	45020 *	1986
Learning representations by back-propagating errors DE Rumelhart, GE Hinton, RJ Williams Nature 323, 533-536	40942 *	1986
Imagenet classification with deep convolutional neural networks A Krizhevsky, I Sutskever, GE Hinton Advances in neural information processing systems, 1097-1105	33787	2012
Learning internal representations by error propagation DE Rumelhart, GE Hinton, RJ Williams	25756	1985

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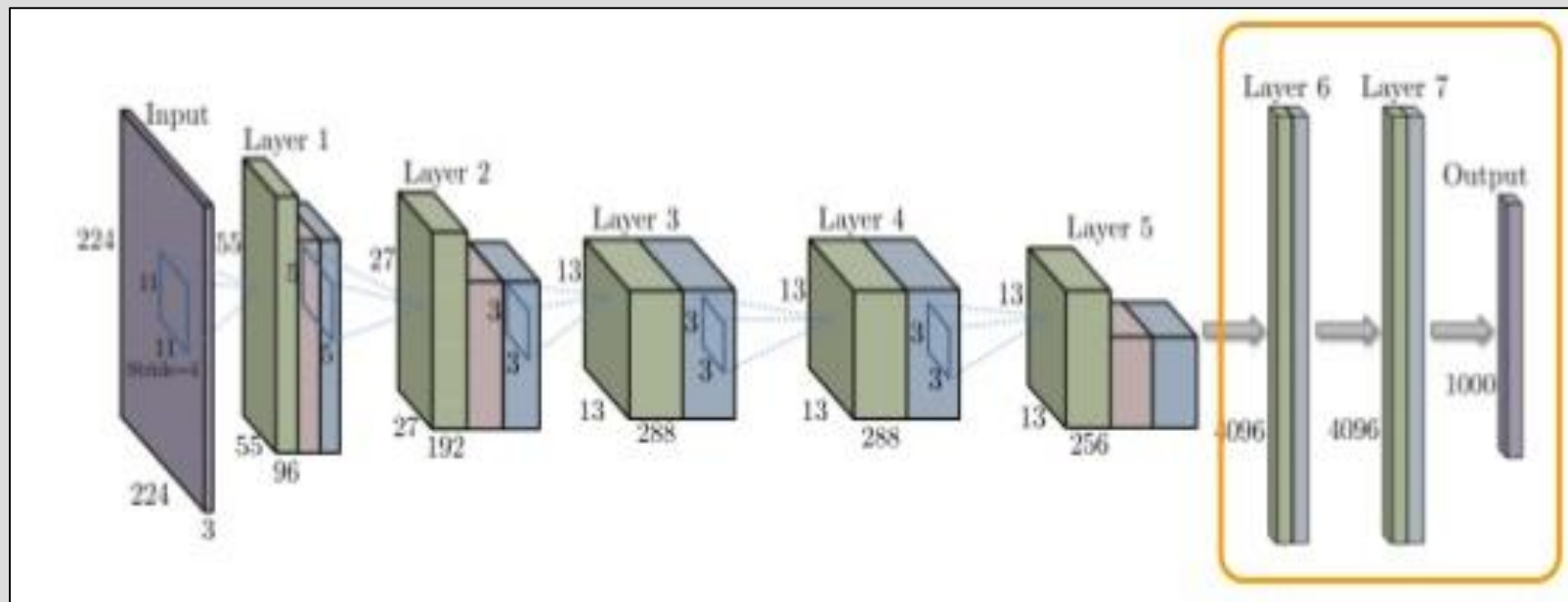


2012 2013 2014 2015 2016 2017 2018 2019



Deep Neural Networks

- Not all deep learning is NN
- DNN are many layers
- Deep Convolutional NN (DCNN) most common
 - AlexNet (1970s resurrected)



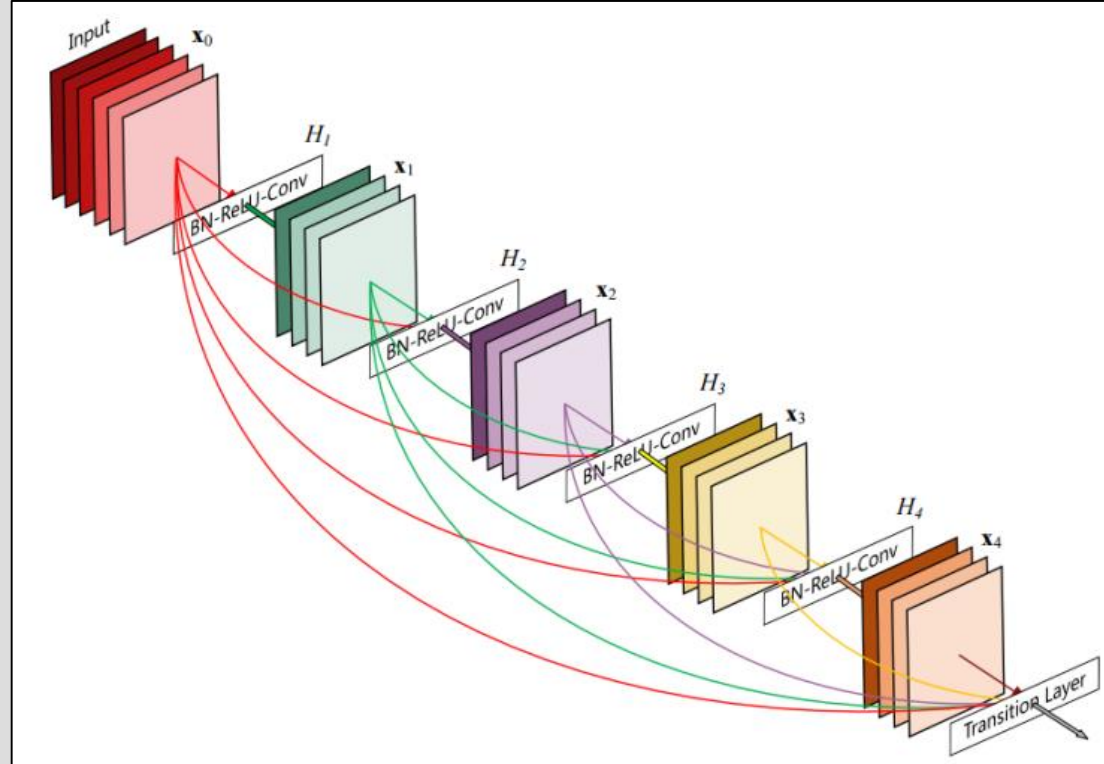
Deep Neural Networks

- Not all deep learning is NN
- DNN are many layers
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 - AlexNet (1970s resurrected)
 - Inception Networks



Deep Neural Networks

- Not all deep learning is NN
- DNN are many layers
- Deep Convolutional NN (DCNN) most common
 - AlexNet
 - Inception Networks
 - Residual Networks

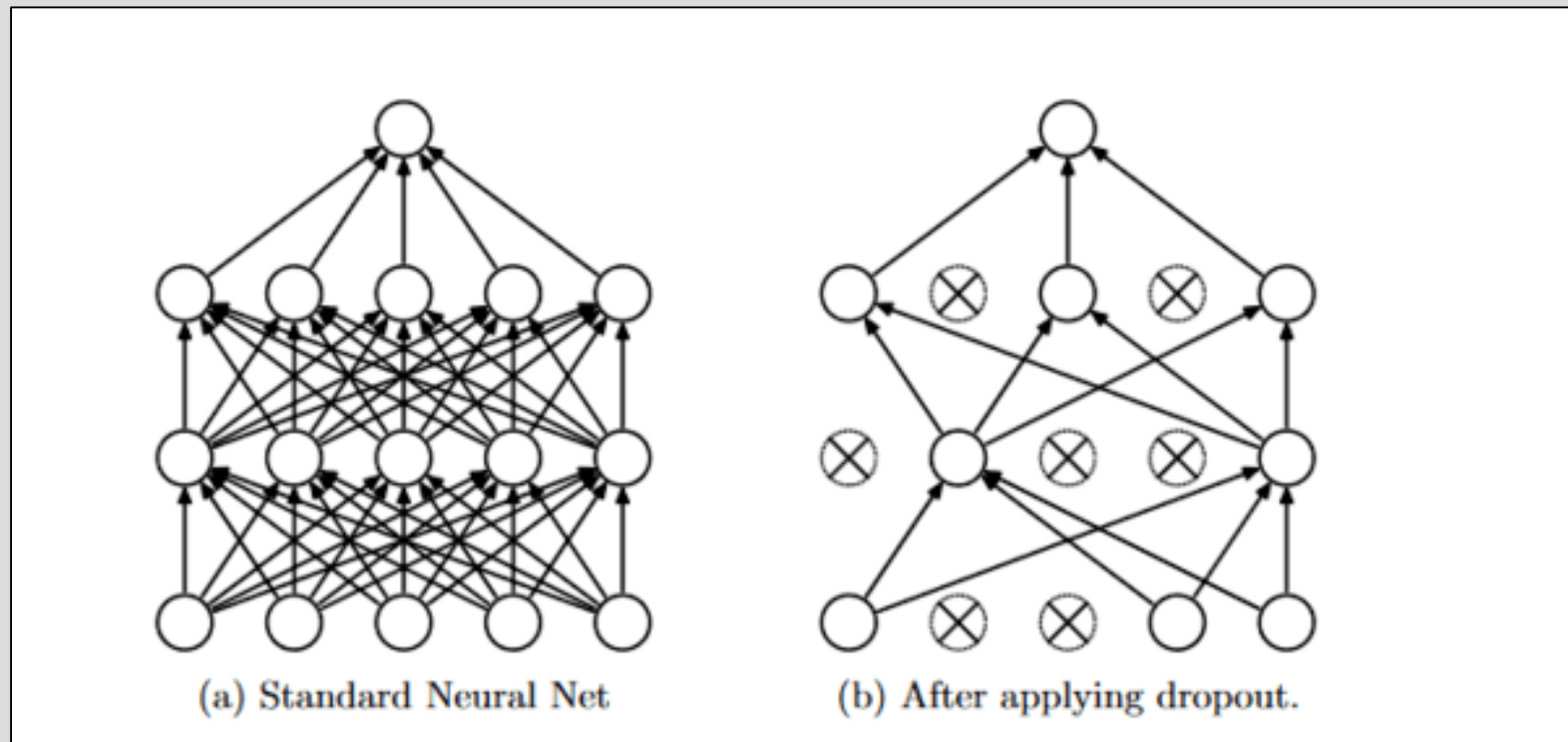


Different Parts

- Dropout
- Nonlinearity
- Pooling
- Batch normalization

Dropout

- Drop neurons at random during training
- Try to avoid overfitting



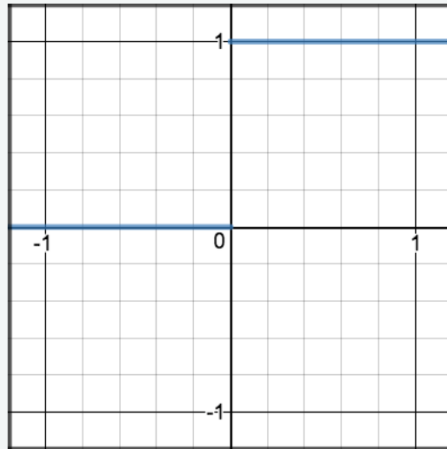
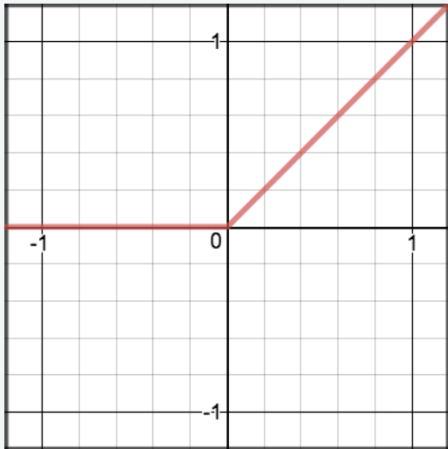
Nonlinearity

Function

$$R(z) = \begin{cases} z & z > 0 \\ 0 & z \leq 0 \end{cases}$$

Derivative

$$R'(z) = \begin{cases} 1 & z > 0 \\ 0 & z \leq 0 \end{cases}$$



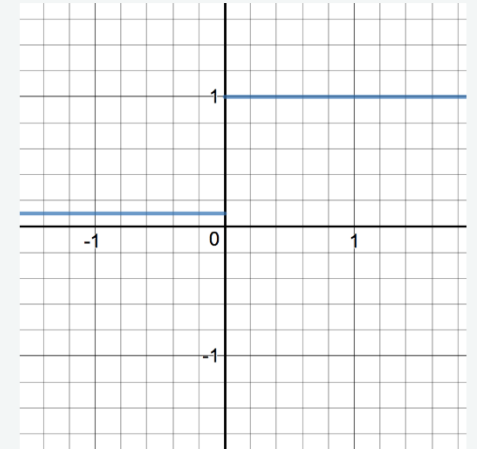
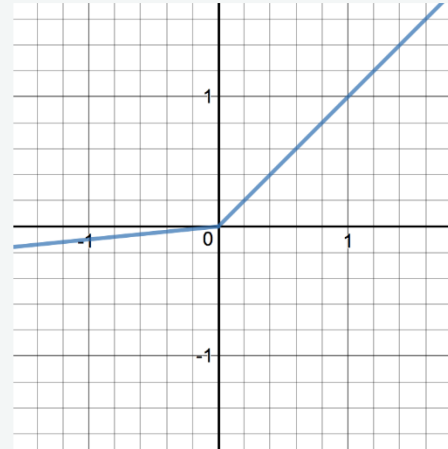
Rectified Linear Units

Function

$$R(z) = \begin{cases} z & z > 0 \\ \alpha z & z \leq 0 \end{cases}$$

Derivative

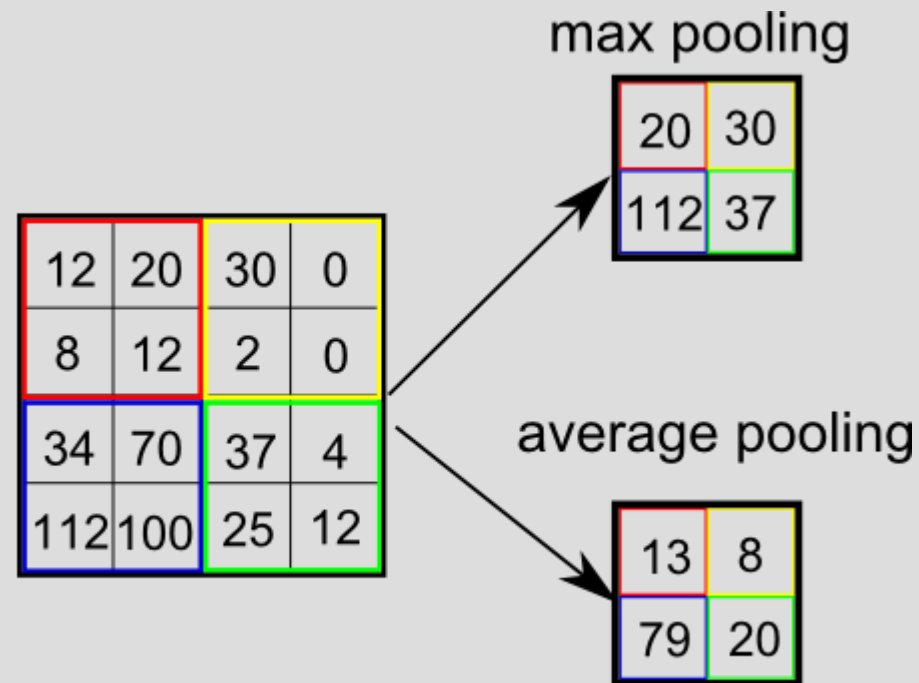
$$R'(z) = \begin{cases} 1 & z > 0 \\ \alpha & z \leq 0 \end{cases}$$



Leaky RELU

Pooling

- Helps address scale, noise, overfitting, etc.



Batch Normalization

- Internal covariate shift
 - Distribution of activations is constantly changing during training
 - Slows down learning
- Do in training
- Remove for testing
- Run before nonlinearity

<https://towardsdatascience.com/batch-normalization-theory-and-how-to-use-it-with-tensorflow-1892ca0173ad>

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;

Parameters to be learned: γ, β

Output: $\{y_i = \text{BN}_{\gamma, \beta}(x_i)\}$

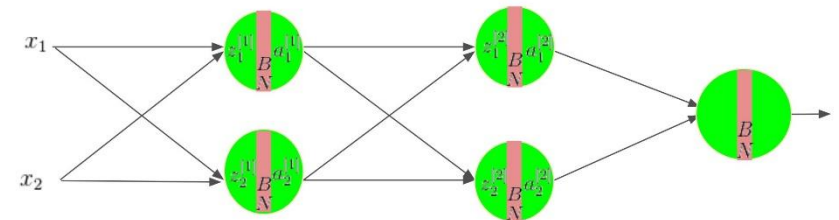
$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i \quad // \text{ mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2 \quad // \text{ mini-batch variance}$$

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \quad // \text{ normalize}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv \text{BN}_{\gamma, \beta}(x_i) \quad // \text{ scale and shift}$$

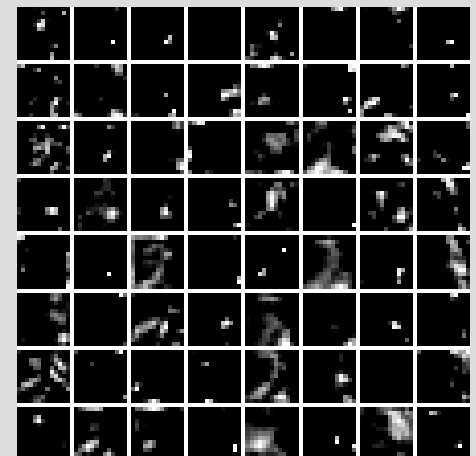
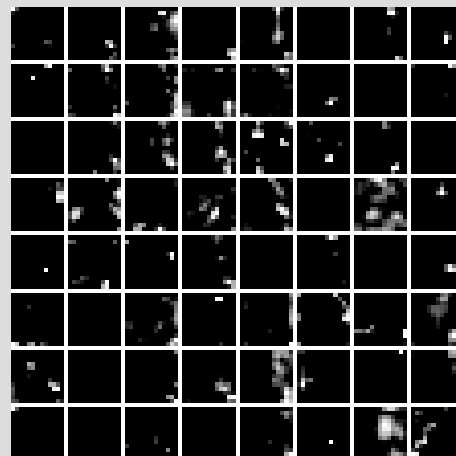
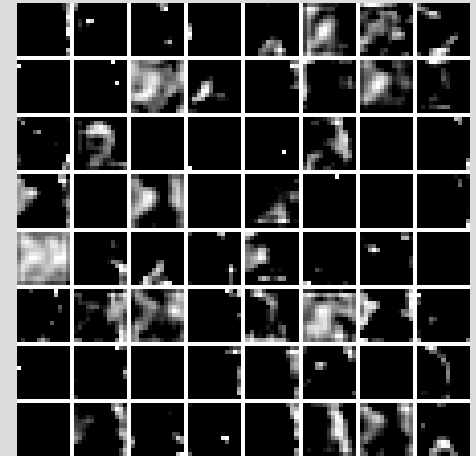
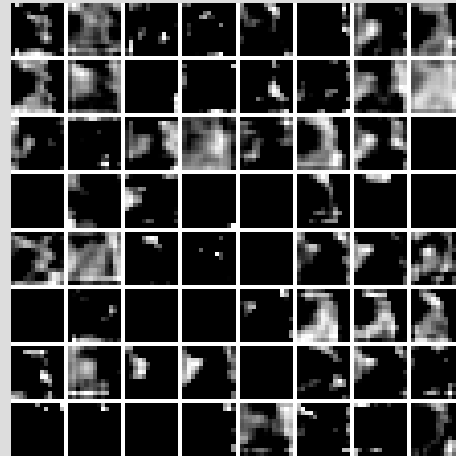
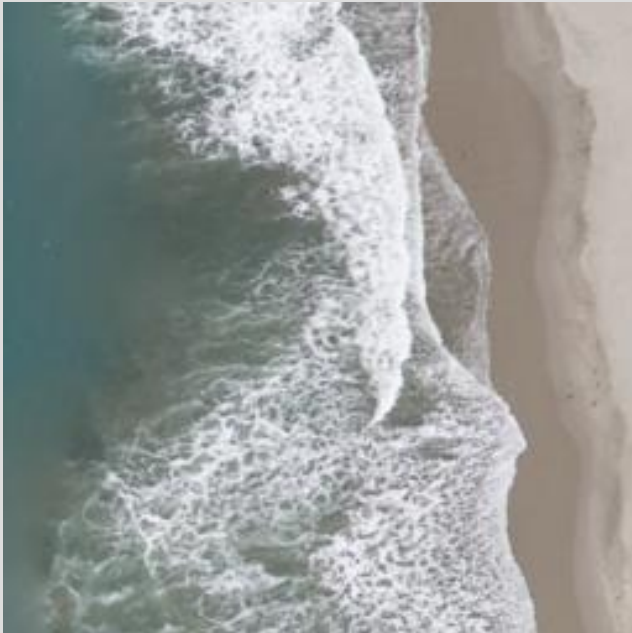
Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.



$$z^{[l]} = W^{[l]} a^{[l-1]} \longrightarrow \begin{aligned} \mu^{[l]} &= \frac{1}{m} \sum_i z^{[l](i)} \\ \sigma^{[l]2} &= \frac{1}{m} \sum_i (z^{[l](i)} - \mu^{[l]})^2 \\ z_{\text{norm}}^{[l](i)} &= \frac{z^{[l](i)} - \mu^{[l]}}{\sqrt{\sigma^{[l]2} + \epsilon}} \\ \tilde{z}^{[l](i)} &= \gamma^{[l]} z_{\text{norm}}^{[l](i)} + \beta^{[l]} \end{aligned} \longrightarrow a^{[l]} = g^{[l]}(\tilde{z}^{[l]})$$

Deep Convolutional NN

- Create layers of feature maps from kernels

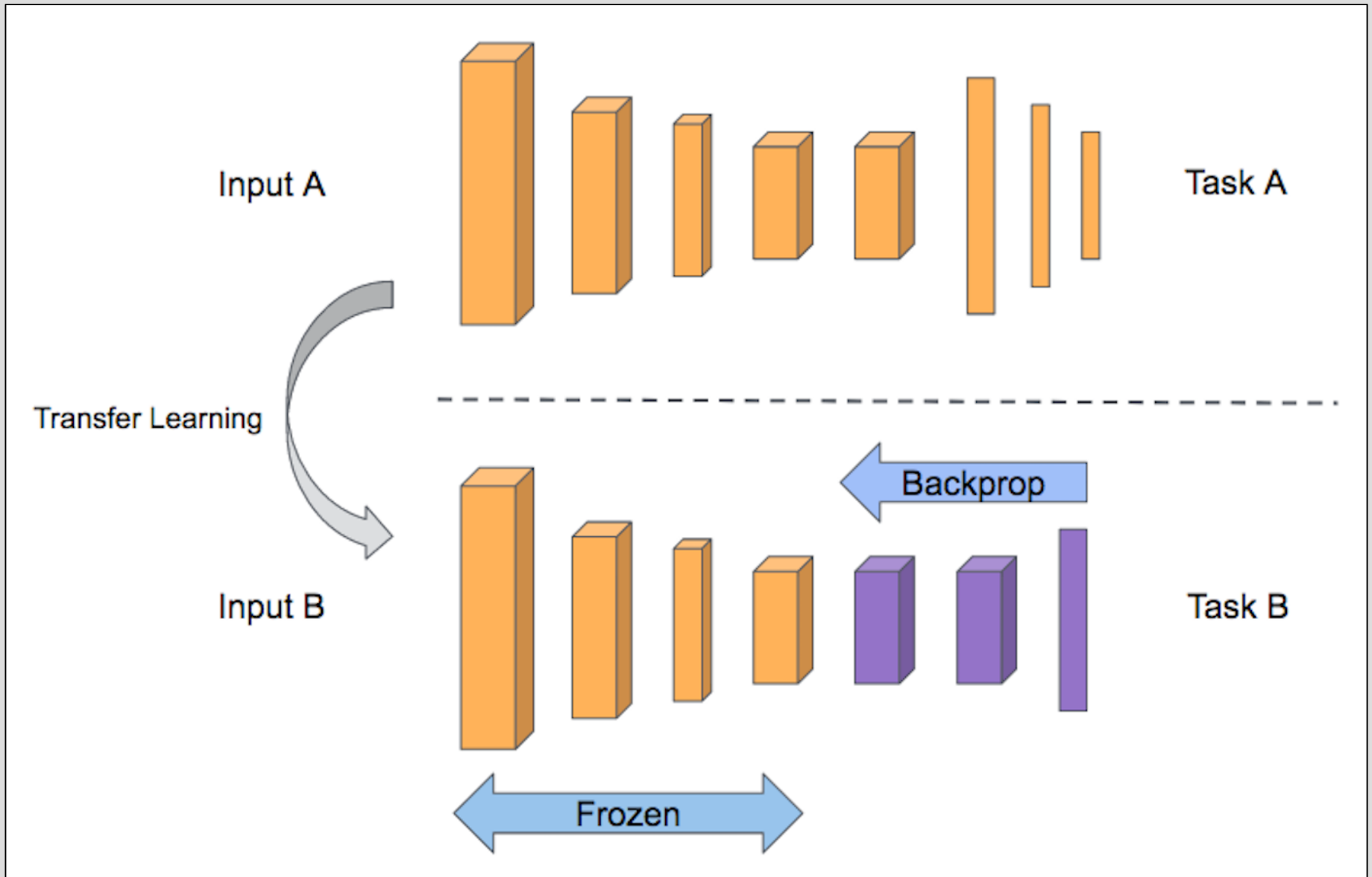


Deep Learning

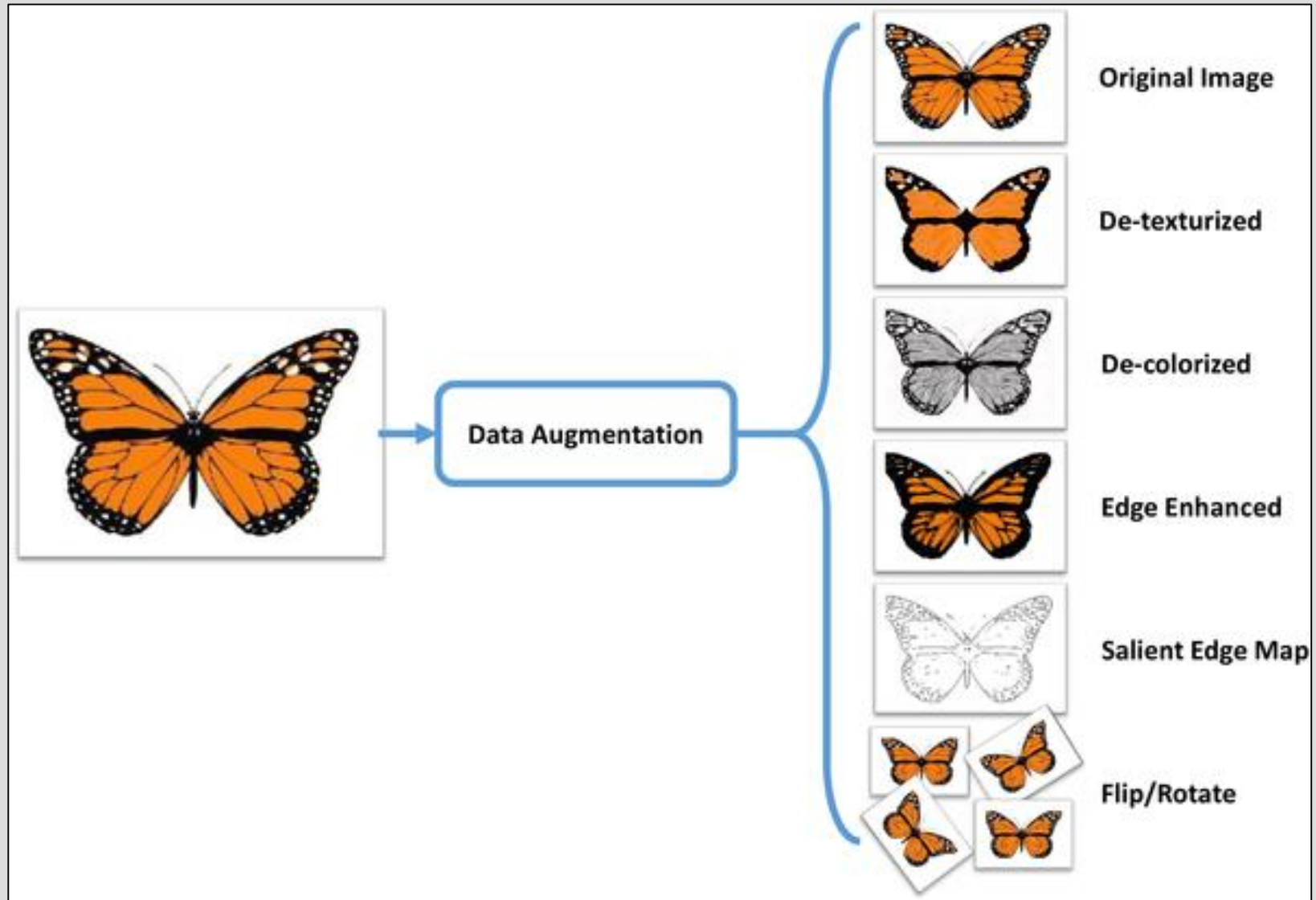
- Typically many many layers/steps of processing
- Learning multiple levels of feature extraction
 - Shallow levels, simple features
 - Working up to more abstract features (concepts)
- https://en.wikipedia.org/wiki/Deep_learning



Transfer Learning



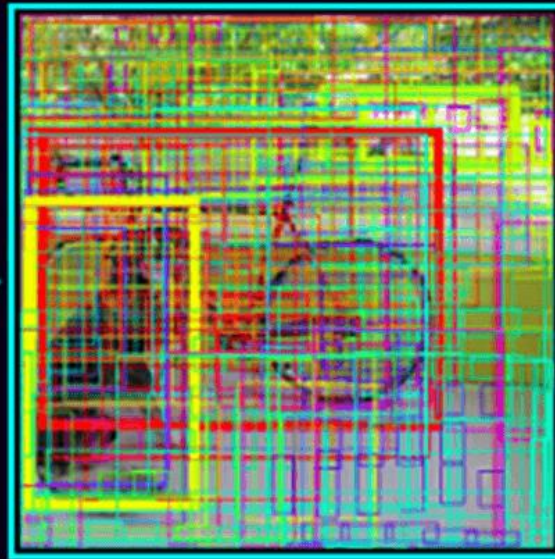
Data Augmentation



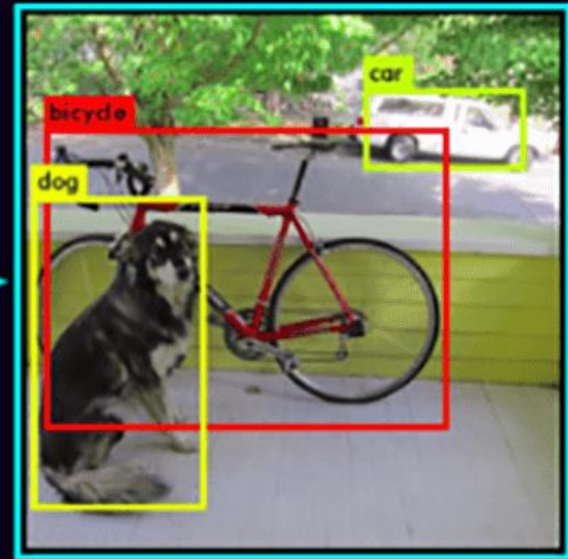
Localization: YOLO and RCNNs and ...



Divide into regions



Detection

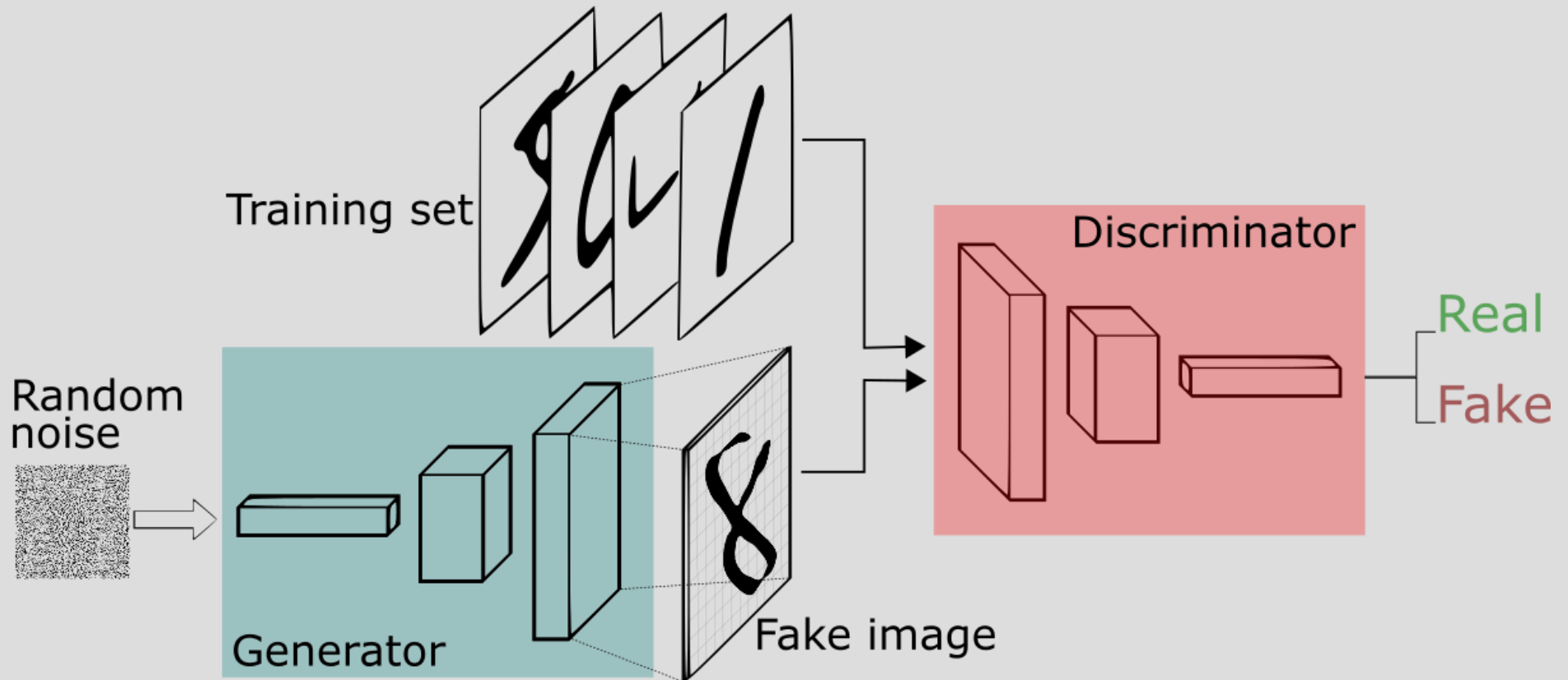


Final decisions

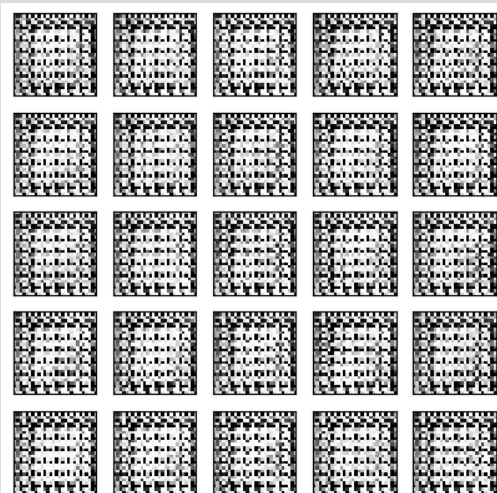


DATA SCIENCE
& ANALYTICS

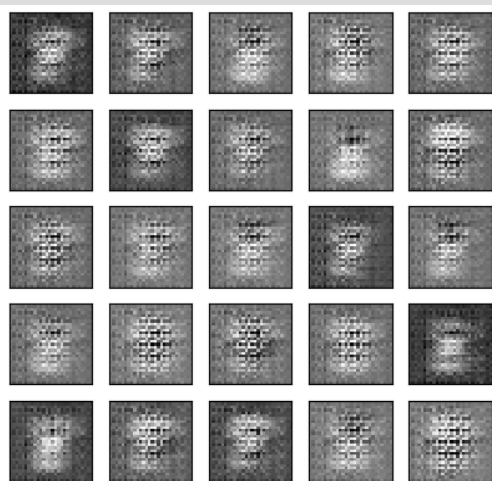
Generative Adversarial Networks



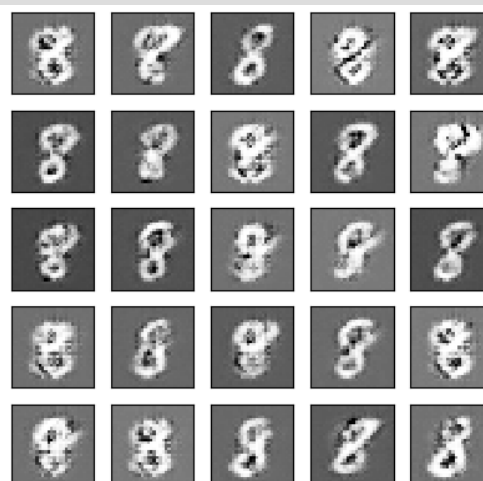
GAN on MINST



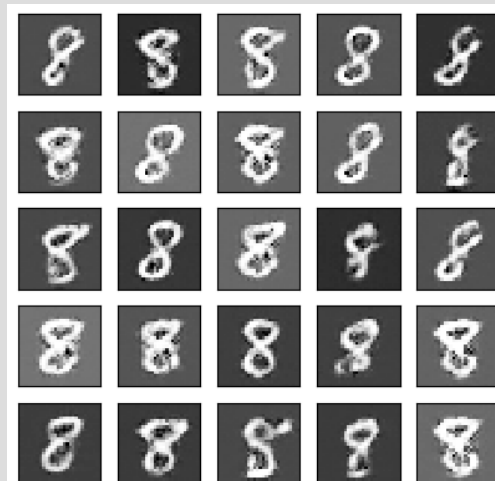
Epoch 1



Epoch 3



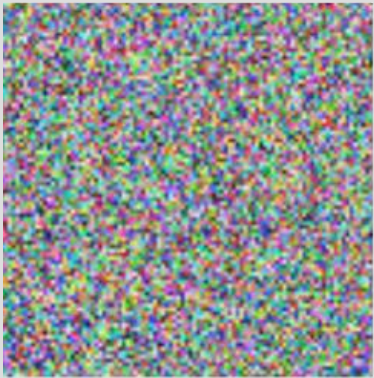
Epoch 10



Epoch 40

Generative Adversarial Networks

Noise $\sim N(0,1)$



Generative
Model



Generative Adversarial Networks

after 5 epochs



after 100 epochs



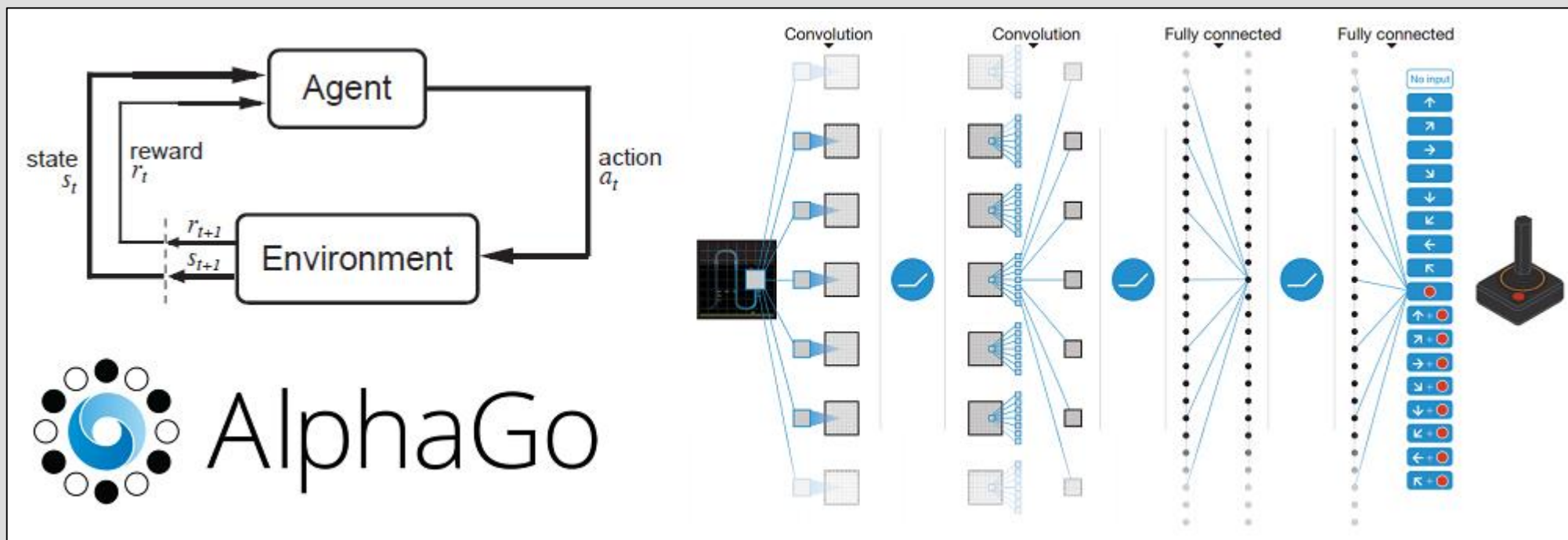


Face Aging

0-18 19-29 30-39 40-49 50-59 60+

The image displays a 3x6 grid of face images, illustrating the aging process for three different individuals. The columns are labeled with age ranges: 0-18, 19-29, 30-39, 40-49, 50-59, and 60+. The rows represent three different individuals. The first row shows a woman with brown hair, the second row shows a man with dark hair, and the third row shows a man with light brown hair. Each row contains six images, one for each age range, showing the progression of facial features and skin texture over time.

Deep Reinforcement Learning



Questions?

