Deep Learning

Inteligencia Artificial en los Sistemas de Control Autónomo
Máster en Ciencia y Tecnología desde el Espacio

Departamento de Automática

Universidad de Alcalá
ISG

Objectives

1. Motivate Deep Learning
2. Introduce main deep architectures
3. Describe state-of-the-art applications

Bibliography

- Géron, Aurélien *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow*. 2nd edition. O'Reilly. 2019

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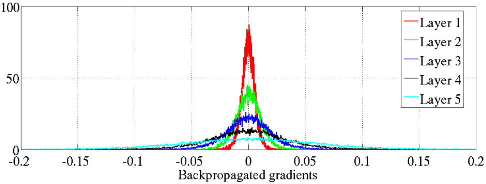
Deep Learning (I)

Deep Learning is not just a network with many layers

- Multiple local optima ⇒ difficult training
- Gradient vanishing



Need of tricks

- Careful weights initialization
- ReLU and Leaky ReLU activation functions
- Regularization through dropout

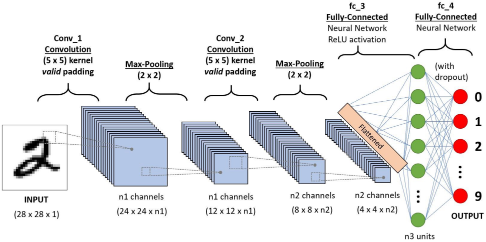
Deep Learning (II)

Two popular types of deep networks

- Convolutional Neural Networks (CNNs) - Image
- Long Short-Term Memory (LSTM) - Time-series and NLP

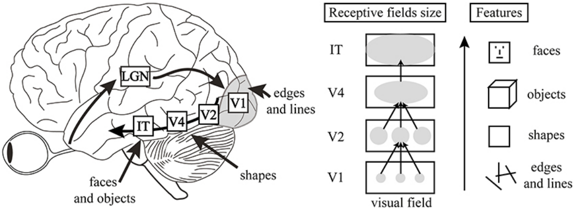
In Deep Learning, we think in laye

- Data input layers
- Output layers
- Fully connected (classic)
- Convolutional layers
- Recurrent layers
- Dropout layers
- More ...



Convolutional Neural Networks

Biological motivation



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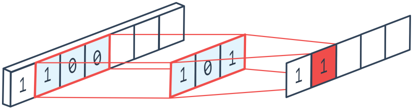
Convolutional Neural Networks

Convolutional layers (I)

CNNs are popular for Computer Vision applications

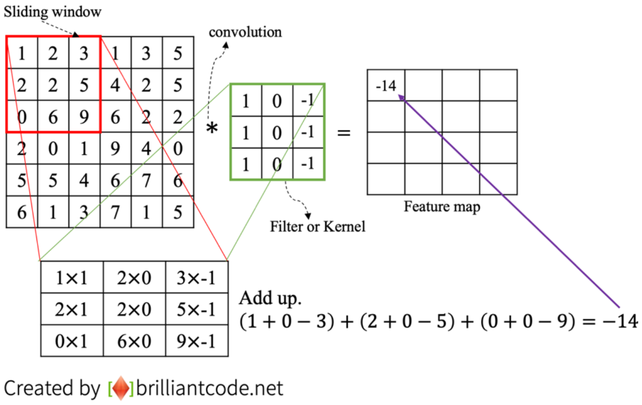
- Networks with convolutional layers
- Convolutions are features extrators
- Its behaviour can be learnt

1D convolution



Convolutional Neural Networks

Convolutional layers (II)



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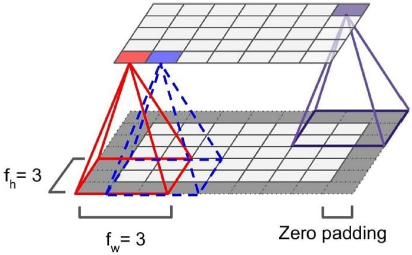
(Conv 2D example)

Convolutional Neural Networks

Convolutional layers (III)

Padding



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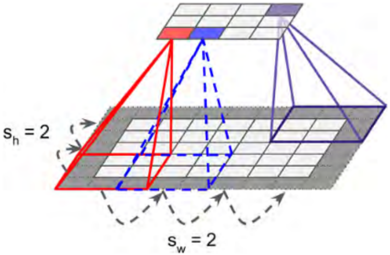
Stride



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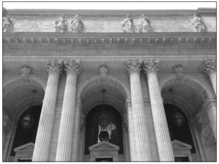
Convolutional Neural Networks

Convolutional layers (IV)

0	0	0
0	1	0
0	0	0

identity



1	0	-1
2	0	-2
1	0	-1

left sobel

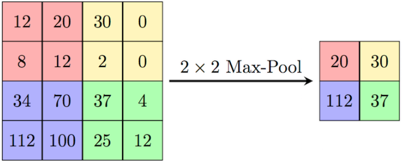
1	2	1
0	0	0
-1	-2	-1

top sobel

(Image kernels)

Convolutional Neural Networks

Max-pooling



Max-pooling down-samples data instances

- Given a matrix, it takes its maximum value
- Usually the matrix is *nxn* (2D)

Benefits

- Dimensionality reduction
- Filters irrelevant information
- Invariant to scale

Convolutional Neural Networks

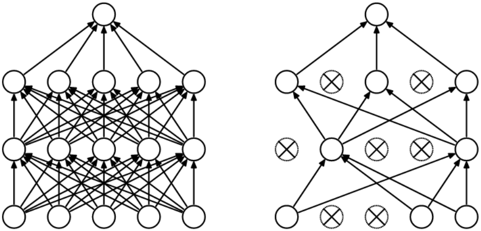
Dropout layer

Dropout is a regularization technique for neural networks

- Dropout deactivates a neuron with probability p for each iteration

Related concept: dense layers

- In Keras, it is just a fully connected layer with regular neurons

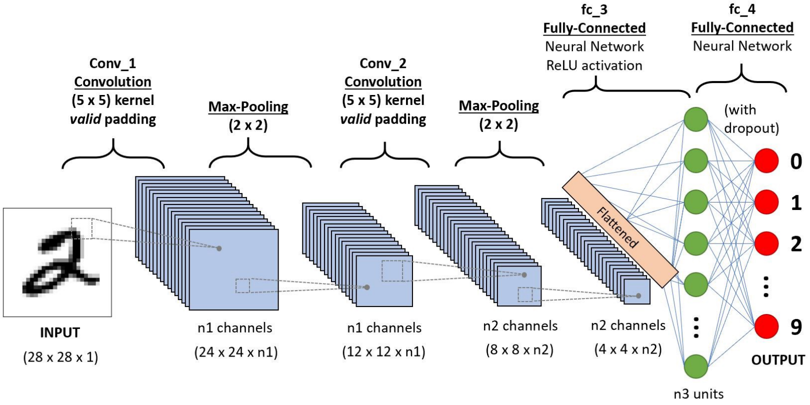


(a) Standard Neural Net (b) After applying dropout.

(Srivastava et al. (2010))

Convolutional Neural Networks

CNN architectures: standard (I)



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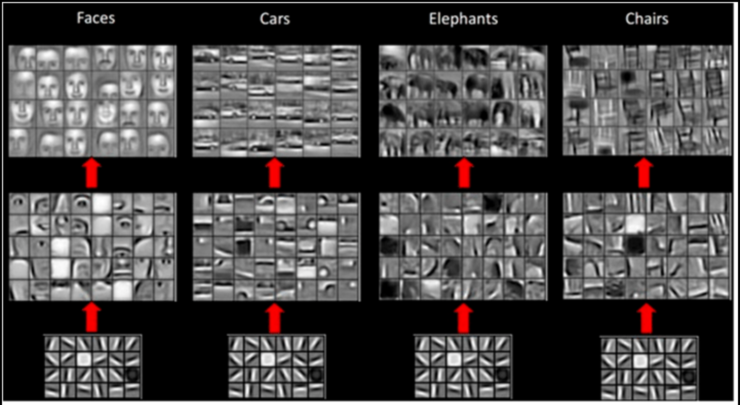
(Demo)

Convolutional Neural Networks

CNN architectures: standard (II)



Convolutional Neural Networks

CNN architectures: other

Other CNN architectures

- LeNet-5
- AlexNet
- GoogLeNet
- VGGNet
- ResNet
- Xception
- SENet

Recurrent networks

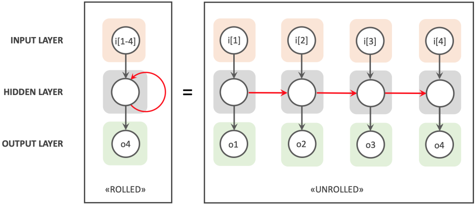
Recurrent neural networks (I)

Recurrent networks have connections pointing backward

- Time-series, NLP, audio, video, ...

Neurons have memory, or **state**

- Named cells
- In basic neurons, state is its output



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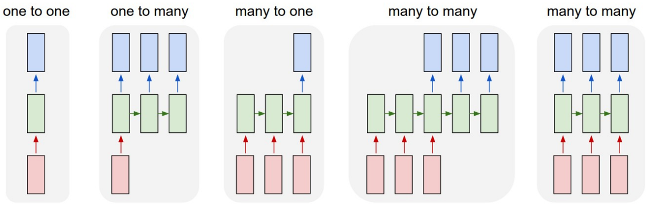
Recurrent networks

Recurrent neural networks (II)



One to many	Many to one	Many to many
vec2seq	seq2vec	seq2seq
Image description	Spam classification Time series forecasting Sentiment score	Machine translation

Recurrent networks

Recurrent neural networks (III)

RNNs problems

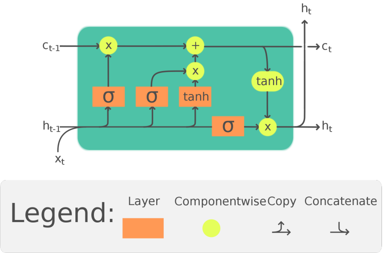
- Gradient unstability
  - Smaller learning rate
  - tanh as activation function
  - Usual DL tricks
- Short memory
  - Information vanishes fast
  - Much more difficult solution

Recurrent networks

LSTM networks

LSTM: Long-Short Term Memory

- Complex cell that improves long-term memory
- Two states: short and long terms
- Very much used as a basic cell
- Much better performance
- Lower training time



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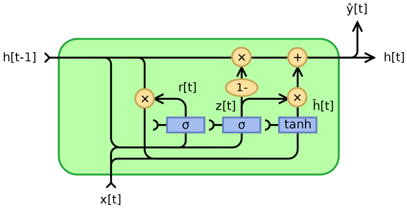
Recurrent networks

GRU

GRU: Gated Recurrent Unit

- Simplification of LSTM
- Seems to perform as well as LSTM



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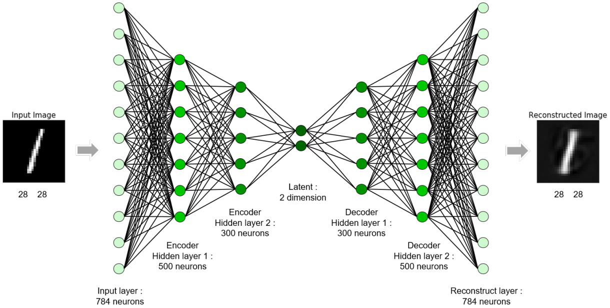
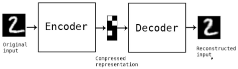
Autoencoders

Autoencoders





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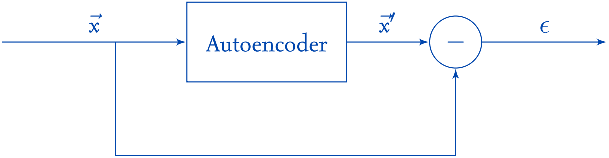
Important concepts: latent space and latent variables

Autoencoders

Autoencoders for anomaly detection (I)



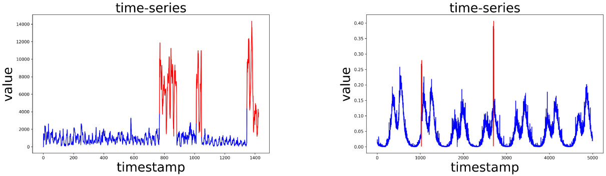
Reconstruction error is an anomality measure

- A norm can be computed to provide a global measure (MAE/MSE), or ...
- ... keep reconstruction error as vector

PCA may be used, less powerfull than autoencoders

Autoencoders

Autoencoders for anomaly detection (II)



(a) (b)

(Source: Niu, Z.; Yu, K.; Wu, X. LSTM-Based VAE-GAN for Time-Series Anomaly Detection. Sensors 2020, 20, 3738.)

Great flexibility to handle reconstruction error

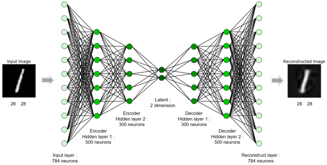
- Trigger an alarm based on a threshold
- Analize the time-series
- Feed a classifier

Autoencoders

Autoencoders as generative models (I)

Any autoencoder may be used as a generative model

- The decoder can reconstruct an instance from a latent space sample



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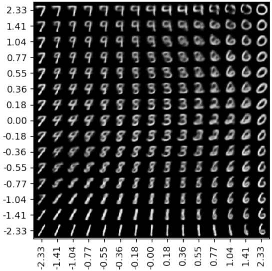

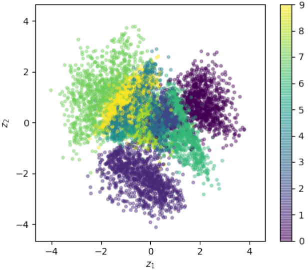

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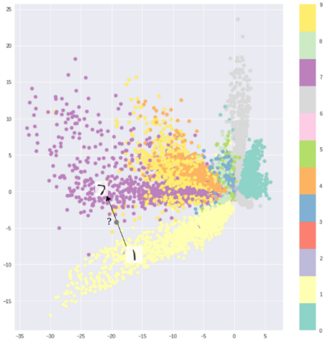
Autoencoders

Autoencoders as generative models (II)

Regular autoencoders are not a good choice for generative models



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Other topics

- Transfer learning
- Data augmentation

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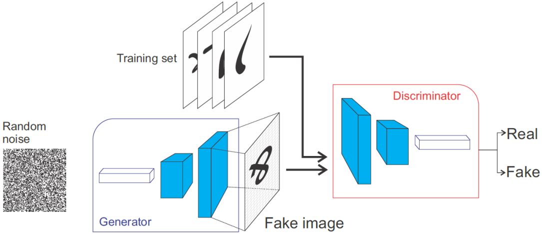
Advanced topics

Generative networks: GAN (I)



(Source) Examples:

- (Faces), (art), (Words), (cats)

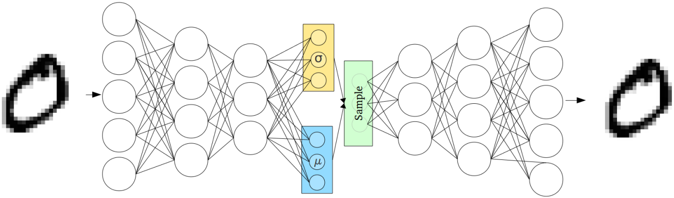
Advanced topics

Generative networks: GAN (II)

GauGAN (Demo)

Advanced topics

Variational Autoencoders (I)



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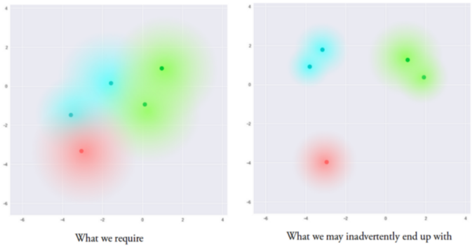
VAEs encodes latent variables as probability distributions

- Gaussian distributions with μ and σ
- Decoder sample the distributions

Advanced topics

Variational Autoencoders (II)



(Source)

We want a structured latent space

- Penalty based on *Kullback-Leibler* (KL) divergence
  - KL measures divergente between two probability distributions

Advanced topics

Variational Autoencoders: semantics (I)

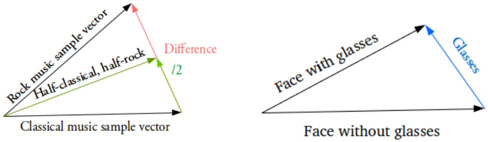
Astonishing VAE feature: latent space has semantics!

(Source)

Advanced topics

Variational Autoencoders: semantics (II)

Another incredible VAE property: 'semantic' arithmetic operations



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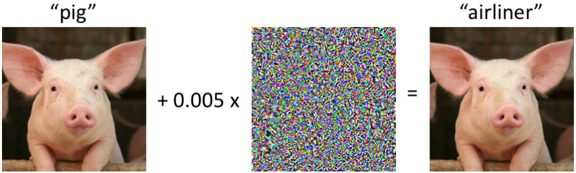
Advanced topics

Adversarial examples



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