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. Define Machine Learning (ML)
2. Delimite ML scope
3. Introduce the main ML tasks
4. Recognize problems as ML tasks

Bibliography

- Bishop, Christopher M. *Pattern Recognition and Machine Learning*. 2nd edition. Springer-Verlag. 2011
- Müller, Andreas C., Guido, Sarah. *Introduction to Machine Learning with Python*. O'Reilly. 2016

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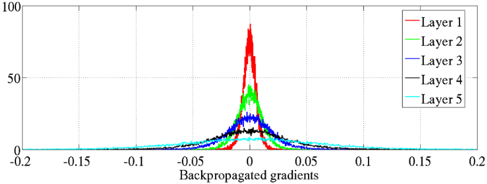
Algorithms

Deep neural networks (I)

Deep Learning is not just a network with many layers

- Gradient vanishing
- Multiple local optima -> difficult training



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Usual solutions

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

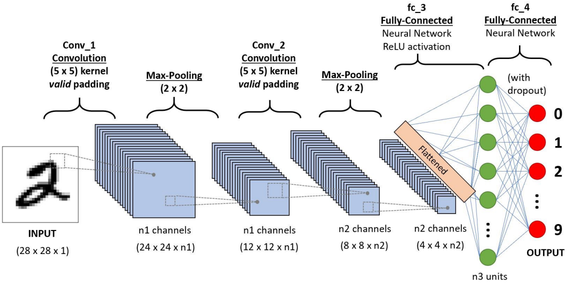
Algorithms

Deep neural networks (II)

Two popular types of deep networks

- Convolutional Neural Networks (CNNs)
- Long Short-Term Memory (LSTM)
- ... we use both

In Deep Learning, we think in layers



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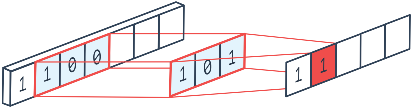
CNNs are popular for Computer Vision applications

- Networks with convolutional layers
- Convolutions in NN use to be 2D
- (Conv 2D example)

Univariable time series are 1D

- 1D convolution



Related concept: deconvolution

Algorithms

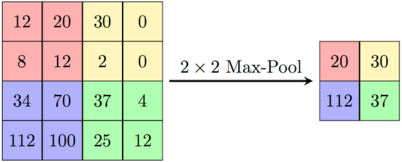
Max-pooling

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



Algorithms

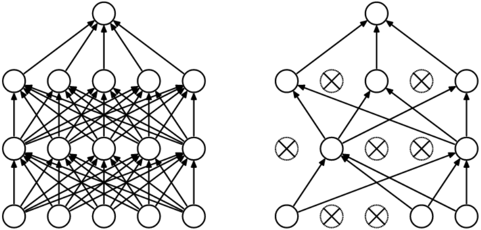
Dropout

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))

LSTM networks

Recurrent neural networks

TODO

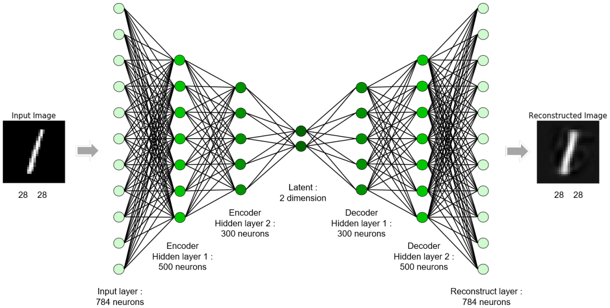
LSTM networks

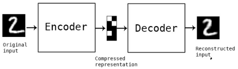
LSTM

TODO

Autoencoders

Autoencoders





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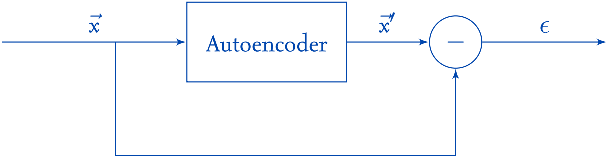
Important concepts: latent space and latent variables

Autoencoders

Autoencoders for anomaly detection (I)



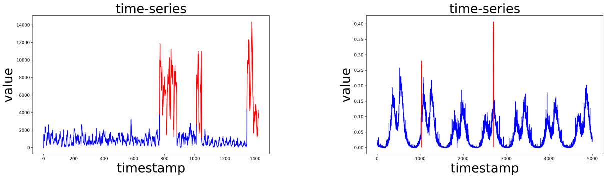
Reconstruction error is an anomality measure

- 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

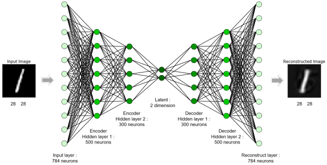
- Trigger an alarm based on a threshold
- Analize the time-series
- Feed a classifier

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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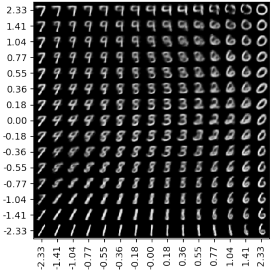

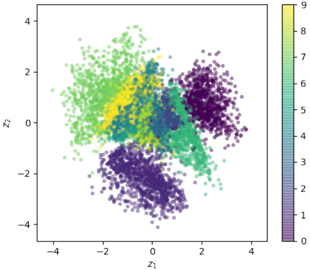

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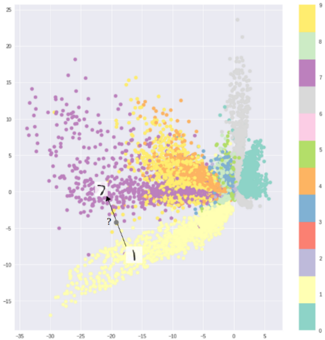
Autoencoders

Autoencoders as generative models (II)

Regular autoencoders are not a good choice for generative models



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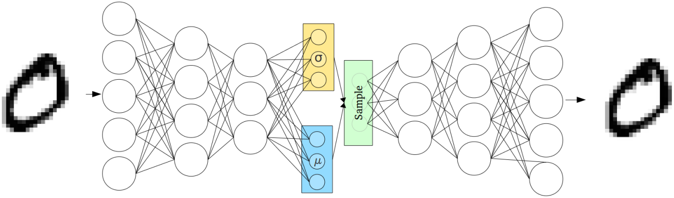
Advanced topics

Variational Autoencoders (I)



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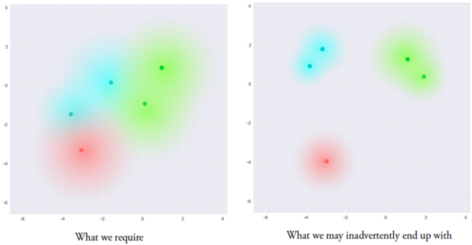
VAEs encodes latent variables as probability distributions

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

Advanced topics

Variational Autoencoders (II)



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We want a structured latent space

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

Advanced topics

VAE semantics (I)

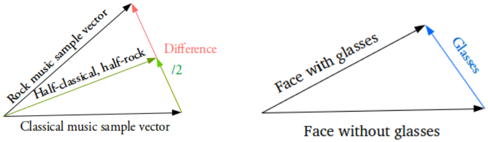
Astonishing VAE feature: latent space has semantics!

(Source)

Advanced topics

VAE semantics (II)

Another incredible VAE property: 'semantic' arithmetic operations



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Advanced topics

GANs
VAEs
Adversarial examples