Deep Learning

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

Departamento de Automática

Objectives

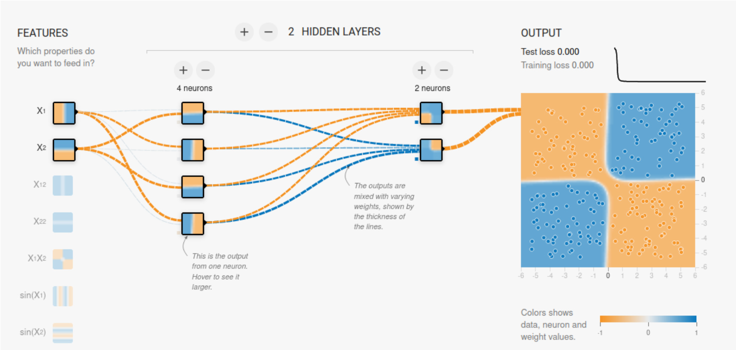
1. Motivate Deep Learning
2. Introduce main deep architectures
3. Describe state-of-the-art applications

Bibliography

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

Table of Contents

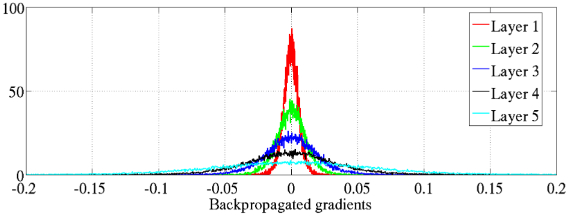
Motivation


FEATURES
Which properties do you want to feed in?
2 HIDDEN LAYERS
4 neurons
2 neurons
OUTPUT
Test loss 0.000
Training loss 0.000
X1
X2
X12
X22
X1X2
sin(X1)
sin(X2)
This is the output from one neuron. Hover to see it larger.
The outputs are mixed with varying weights, shown by the thickness of the lines.
Colors shows data, neuron and weight values.

Deep Learning (I)

Deep Learning is not just a network with many layers

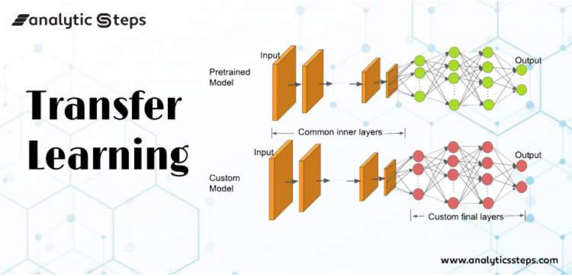
- High number of parameters to optimize
- More layers ⇒ more local optima ⇒ more difficult training
- Large datasets
- Gradient vanishing / exploding



Deep Learning (II)

Need of tricks to train deep networks

- Unsupervised pretraining
- Careful weights initialization
  - Glorot and He initialization, LeCun initialization
- Non-saturating activation functions
  - Sigmoid activation is problematic
  - ReLU and Leaky ReLU activation functions
- Transfer learning/ pretained models



(Source)

Deep Learning (III)

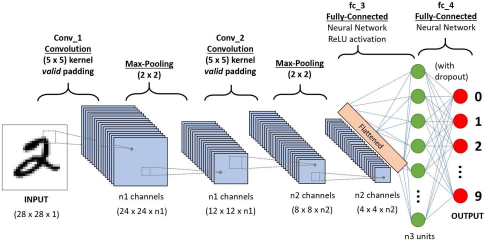
- Batch normalization
- Regularization
  - L1, L2 and dropout
- Faster optimizers
  - AdaGrad, Adam, RMSProp
- Data augmentation
  - Creates modified copies of the dataset
  - It increases the number of samples
- Clever design of the network to minimize parameters

(Source)

Deep Learning (IV)

In Deep Learning, we use to think in layers

- Data input layers
- Output layers
- Fully connected (or dense)
- Convolutional layers
- Max-pooling
- Recurrent layers
- Dropout layers
- More ...

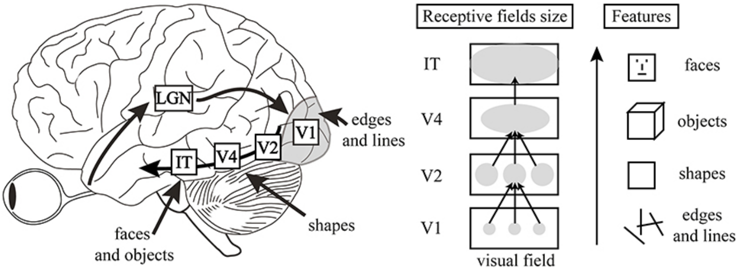


Two popular types of deep architectures

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

Convolutional Neural Networks

Biological motivation



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Convolutional Neural Networks

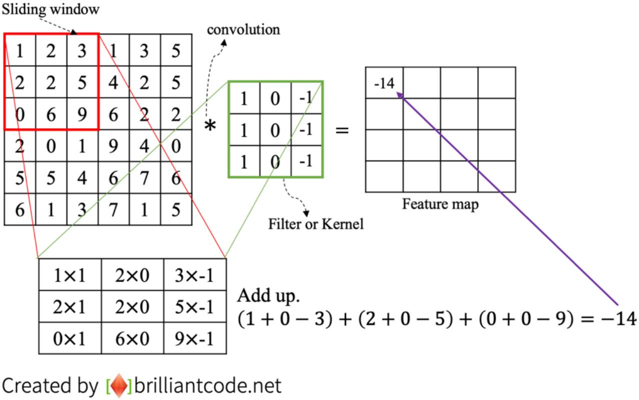
Convolutional layers (I)

CNNs are popular for Computer Vision applications

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

Convolutional Neural Networks

Convolutional layers (II)



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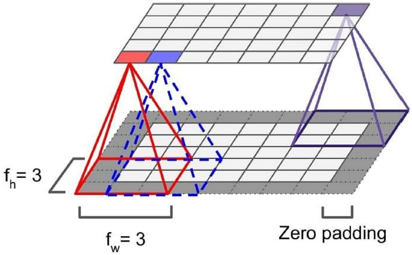
(Conv 2D example)

Convolutional Neural Networks

Convolutional layers (III)

Padding



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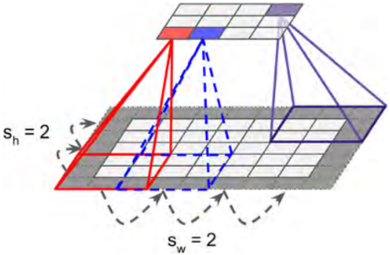
Stride



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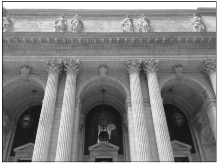
Convolutional Neural Networks

Convolutional layers (IV)

0	0	0
0	1	0
0	0	0

identity



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

left sobel

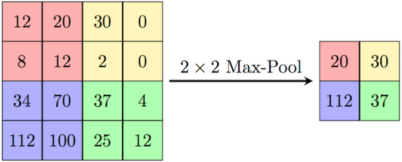
1	2	1
0	0	0
-1	-2	-1

top sobel

(Image kernels)

Convolutional Neural Networks

Max-pooling layer



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

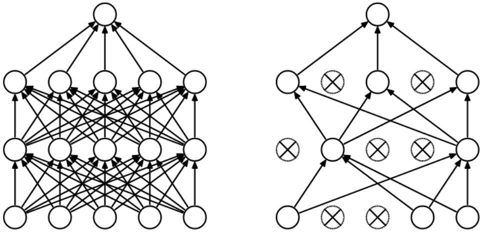
Dropout layer

Dropout is a regularization technique for neural networks

- Applied during trainning
- 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

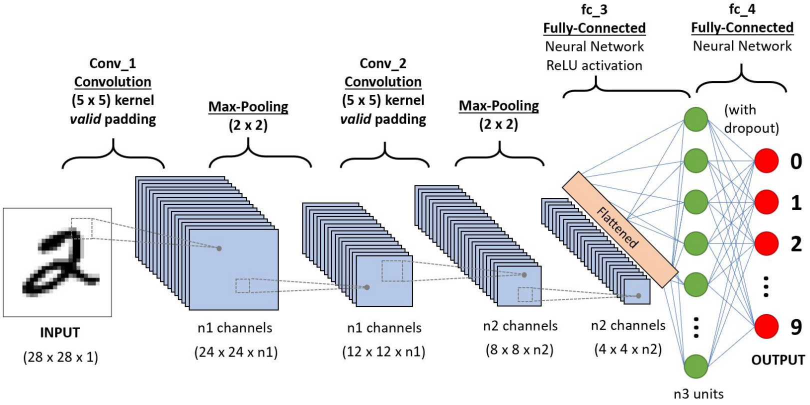


(a) Standard Neural Net (b) After applying dropout.

(Srivastava et al. (2010))

Convolutional Neural Networks

CNN architectures: standard (I)



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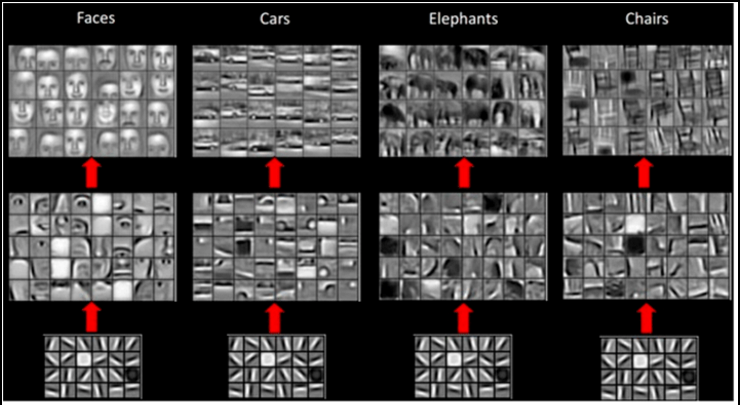
(Demo)

Convolutional Neural Networks

CNN architectures: standard (II)



Convolutional Neural Networks

Other CNN architectures

Other CNN architectures

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

Performance on Imagenet

Model	Acc.	Parameters	Depth
VGG16	0,901	138,357,544	23
InceptionV3	0,937	23,851,784	159
ResNet50	0,921	25,636,712	-
Xception	0,945	22,910,480	126

Famous generative deep networks

Model	Parameters
GTP-2	1.5 billion (1,500,000,000)
GTP-3	175 billion (175,000,000,000)
GPT-4	1.5 trillion

Convolutional Neural Networks

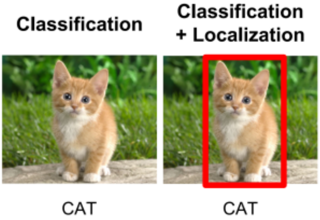
Classification and localization

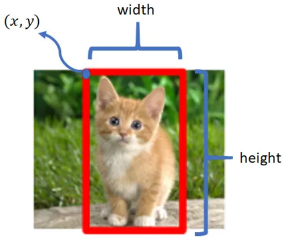
Localization: Predict a bounding box around the object

- Classification as a regression problem: X, Y, width and height
- Four output units per class

We need annotation tools

- (VGG Image annotator), (LabelImg), (ImgLab)





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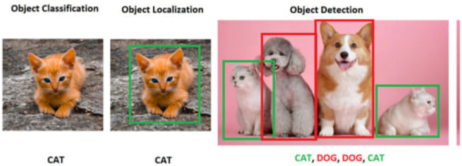
Convolutional Neural Networks

Object detection

Object detection: Classify and localize multiple objects in an image



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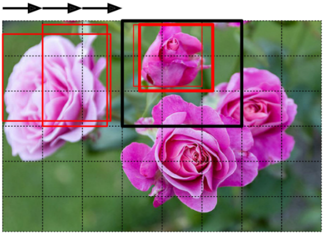


Old approach: Slide across a single object CNN

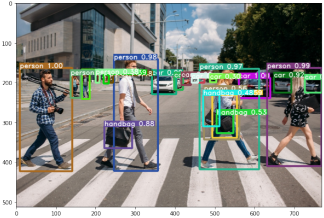
- The image must pass through the CNN several times
- Bad for real-time applications

Convolutional Neural Networks

Object detection: You Only Look Once (YOLO)

YOLO is a fast architecture for real-time object detection

- Several versions proposed by different teams
- Valid for video object detection
- Several implementations
- (Yolo v8)
- YOLO supports image segmentation



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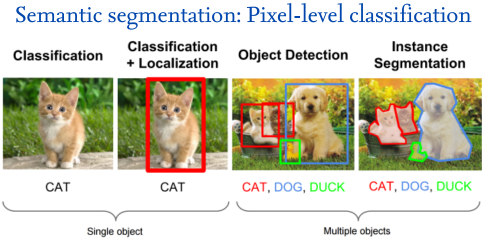
Convolutional Neural Networks

Semantic segmentation



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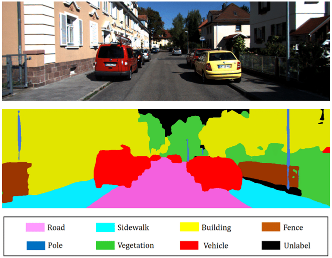

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Recurrent networks

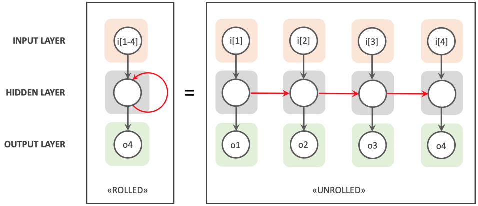
Recurrent neural networks (I)

Recurrent networks have connections pointing backward

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

Neurons have memory, or **state**

- Named cells
- In basic neurons, state and output are the same



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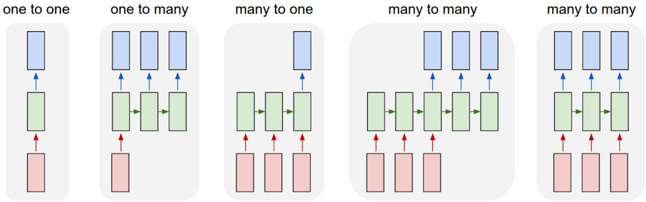
Recurrent networks

Recurrent neural networks (II)

Sequence learning



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

Recurrent networks

Recurrent neural networks (III)

RNNs problems

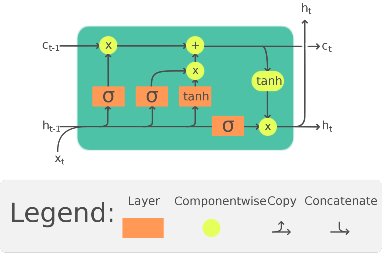
- Gradient unstability
    - Smaller learning rate
    - tanh as activation function
    - Usual DL tricks
- Short memory
    - Information vanishes fast
    - Much more difficult solution

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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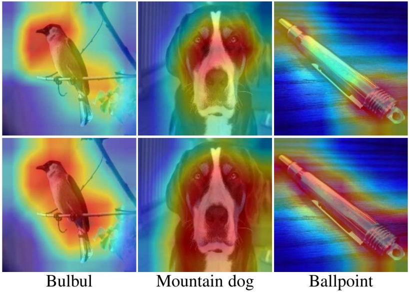
Recurrent networks

Advanced architectures

- Attention networks
- Transformers (and visual transformers)
- Encoder-decoder architectures



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Recurrent networks

RNNs cool applications: language generation with a LSTM

Shakespeare

```
PANDARUS:
Alas, I think he shall be come
approached and the day
When little srain would be
attain'd into being never fed,
And who is but a chain and
subjects of his death,
I should not sleep.
Second Senator:
They are away this miseries,
produced upon my soul,
Breaking and strongly should
be buried, when I perish
The earth and thoughts of
many states.
```

Cervantes

```
-pero me manda mal -respondió
el maererlino, que yo no será
mejor que se ha de ser de don
quijote, que no le
acompañasen, se vengaban de
haber tenido al cabo de los
cuales se venció de su escudero,
y el infierno que todos los
pasaron su hermosura, y a mí
me parece que se cuenta el
yelmo de la caballería, don
gregorio de la similacada al
caballo que de la mano, según la
señora dulcinea del toboso.
-no es bien -respondió sancho-,
```

Recurrent networks

RNNs cool applications: music synthesis

DeepBach

- (Video)
- (Paper)
- (Code)

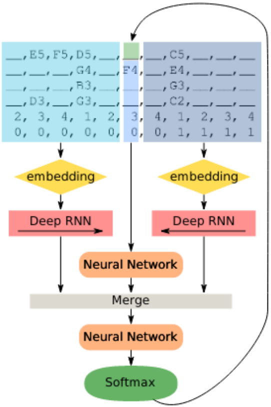

Figure 4. Graphical representations of DeepBach's neural network architecture for the soprano prediction p_1.

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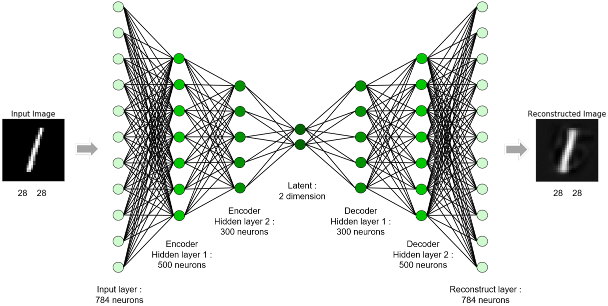
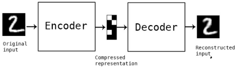
Autoencoders

Autoencoders





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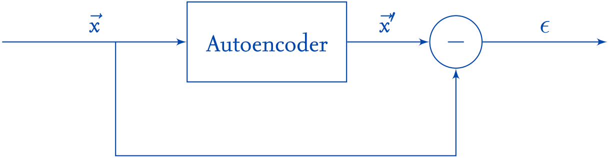
Important concepts: latent space and latent variables

Autoencoders

Autoencoders for anomaly detection (I)



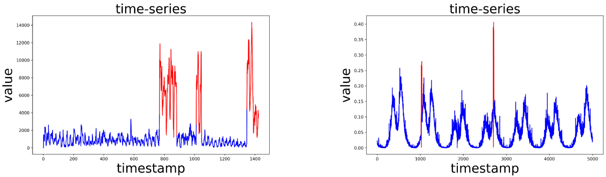
Reconstruction error is an anomality measure

- 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

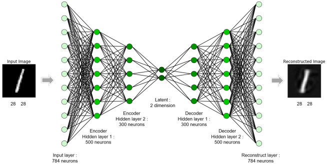
- Trigger an alarm based on a threshold
- Analize the time-series
- Feed a classifier

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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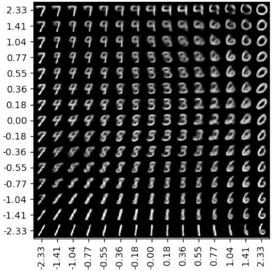

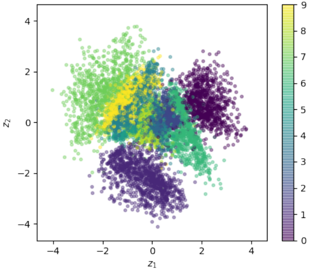

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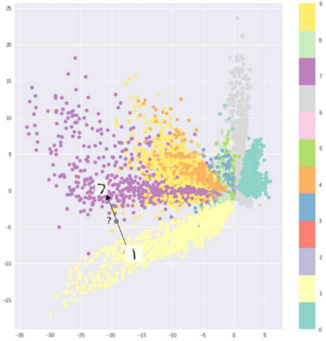
Autoencoders

Autoencoders as generative models (II)

Regular autoencoders are not a good choice for generative models



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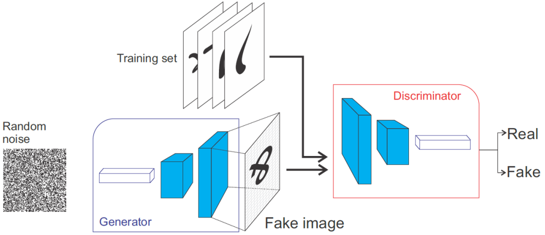
Advanced topics

Generative networks: GAN



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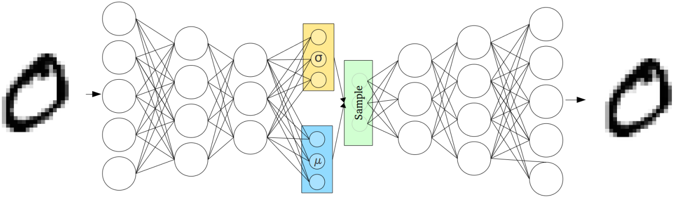
Examples:

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

Advanced topics

Variational Autoencoders



(Source)

VAEs encodes latent variables as probability distributions

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

Advanced topics

Variational Autoencoders (II)

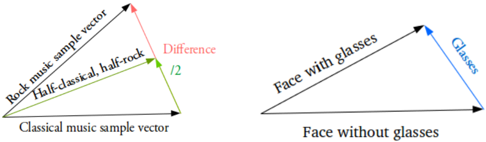
Astonishing feature: latent space has semantics!

(Source)

Advanced topics

Variational Autoencoders: semantics (II)

Another incredible property: ‘semantic’ arithmetic operations



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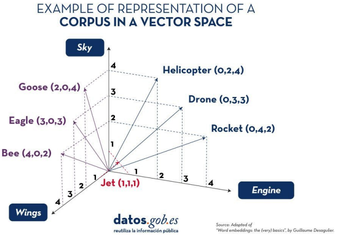
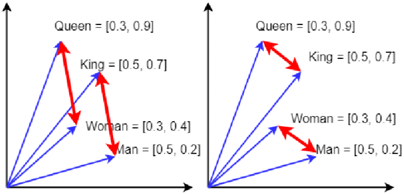
Advanced topics

Word embeddings





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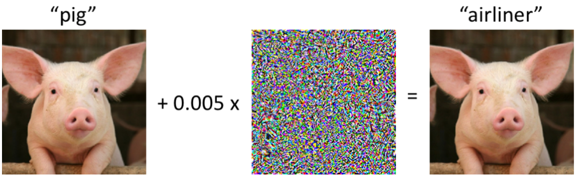
(Embedding Projector)

Advanced topics

Adversarial examples



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