

Demystifying Artificial Intelligence Sorcery

(Part 3: Deep Learning)^a

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^aAvailable @ <https://github.com/a-mhamdi/jlai/>



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ROADMAP

1. An overview
2. Convolutional Neural Network
3. Generative Adversarial Network
4. Variational Autoencoder
5. Natural Language Processing
6. Transfer Learning
7. Reinforcement Learning
8. Quizzes

An overview

- CNNs** (*Convolutional Neural Networks*) are used for image classification and other computer vision tasks because they are able to automatically learn features from raw data. This is useful for tasks where manual feature engineering is difficult or impractical.
- GANs** (*Generative Adversarial Networks*) are used for tasks such as image generation and data augmentation because they are able to generate new data samples that are similar to a given dataset.
- VAEs** (*Variational Autoencoders*) are used for tasks such as image generation and anomaly detection because they are able to learn a compact representation of a dataset and generate new samples from this representation.
- NLP** (*Natural Language Processing*) is important for tasks such as language translation, text classification, and language generation because it allows computers to process and understand human language.

Convolutional Neural Network

CNN

MOTIVATING FACTORS

- ▶ A **Convolutional Neural Network (CNN)** is a type of neural network that is particularly well-suited for image classification and object recognition tasks. It is designed to process data with a grid-like topology, such as an image,.
 - ▶ **CNNs** are composed of several types of layers, including convolutional layers, pooling layers, and fully connected layers.
- ❶ The **convolutional layers** apply filters to the input data, which are used to detect patterns and features in the data.
 - ❷ The **pooling layers** reduce the spatial dimensions of the data, which helps to reduce the complexity of the model and make it more robust to small translations of the input data.
 - ❸ The **fully connected layers** combine the features learned by the convolutional and pooling layers to make a prediction.

CNN

APPLICATIONS

Image classification CNNs can be used to classify images into different categories, such as identifying objects in an image or labeling the scene depicted in an image.

Object detection CNNs can be used to detect objects in images or videos and to localize them by drawing bounding boxes around them.

Image segmentation CNNs can be used to segment images into different regions, such as separating the foreground from the background or labeling different objects in an image.

Medical image analysis CNNs have been used to analyze medical images, such as CT scans and X-rays, for tasks such as tumor detection and segmentation.

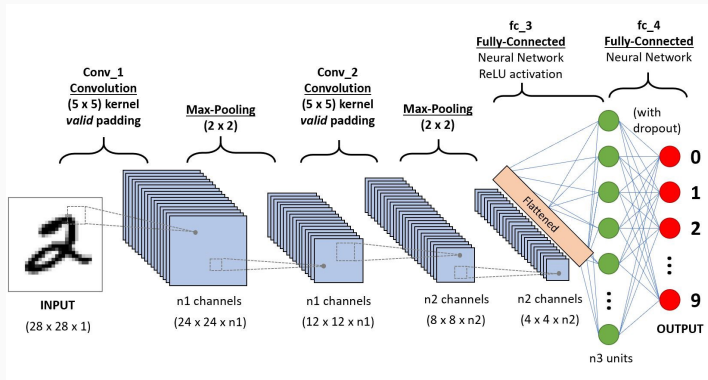
Self-driving cars CNNs have been used to process camera images in self-driving cars to detect pedestrians, other vehicles, and traffic signals.

Robotics CNNs have been used to process images from robots to enable them to navigate their environment and perform tasks such as grasping objects.

Natural language processing CNNs have been used to process text data for tasks such as sentiment analysis and language translation.

CNN

ARCHITECTURE


[Source](#)

CNN

IMAGE KERNELS

Image Kernels explained · x +

setosa.io/ev/image-kernels/

By [Victor Powell](#)

An image kernel is a small matrix used to apply effects like the ones you might find in Photoshop or Gimp, such as blurring, sharpening, outlining or embossing. They're also used in machine learning for 'feature extraction', a technique for determining the most important portions of an image. In this context the process is referred to more generally as "convolution" (see: [convolutional neural networks](#).)

To see how they work, let's start by inspecting a black and white image. The matrix on the left contains numbers, between 0 and 255, which each correspond to the brightness of one pixel in a picture of a face. The large, granulated picture has been blown up to make it easier to see; the last image is the "real" size.

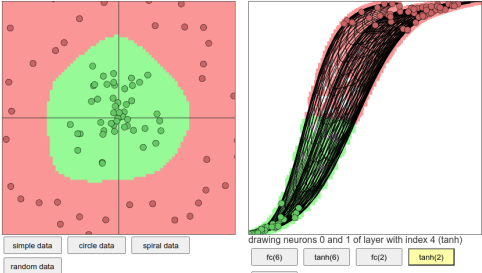
<https://setosa.io/ev/image-kernels/>

CNN

CONVNETJS DEMO

Feel free to change this, the text area above gets eval()'d when you hit the button and the network gets reloaded. Every 10th of a second, all points are fed to the network multiple times through the trainer class to train the network. The resulting predictions of the network are then "painted" under the data points to show you the generalization.

On the right we visualize the transformed representation of all grid points in the original space and the data, for a given layer and only for 2 neurons at a time. The number in the bracket shows the total number of neurons at that level of representation. If the number is more than 2, you will only see the two visualized but you can cycle through all of them with the cycle button.



simple data circle data spiral data
random data

Controls:
CLICK: Add red data point
SHIFT+CLICK: Add green data point
CTRL+CLICK: Remove closest data point

Go [back to ConvNetJS](https://cs.stanford.edu/people/karpathy/convnetjs/)

drawing neurons 0 and 1 of layer with index 4 (tanh)
 fc(6) tanh(6) fc(2) **tanh(2)**
 fc(2)
 cycle through visualized neurons at selected layer (if more than 2)

<https://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html>



Code is available at <https://github.com/a-mhamdi/jlai/>

→ *Codes* → *Julia* → *Part-3* → *cnn.jl*



Generative Adversarial Network

GAN

AN OVERVIEW

- ▶ A **Generative Adversarial Network (GAN)** is a type of deep learning model designed to generate new, synthetic samples of data. It consists of two networks: a **generator network** and a **discriminator network**. The **generator network** generates synthetic samples, while the **discriminator network** tries to distinguish between the synthetic samples and real samples of data.
- ▶ During training, the **generator and discriminator networks** are trained concurrently, with the **generator** trying to generate synthetic samples that are indistinguishable from real samples, and the **discriminator** trying to correctly classify the samples as either real or synthetic. The **generator** is trained to improve its synthetic samples based on the feedback from the **discriminator**, and the **discriminator** is trained to become more sensitive to synthetic samples.
- ▶ The goal of a **GAN** is to learn a generative model that can produce synthetic samples that are similar to the training data. **GANs** have been used for a variety of tasks, including image generation, audio synthesis, and natural language processing.

GAN

APPLICATIONS

Image generation GANs can be used to generate realistic images of objects, people, and scenes.

Image style transfer GANs can be used to transfer the style of one image to another image, while preserving the content of the original image.

Text-to-image synthesis GANs can be used to generate images from textual descriptions, such as generating images of objects based on their names.

Video prediction GANs can be used to predict future frames in a video, given the past frames.

Text-to-speech synthesis GANs can be used to generate speech audio from text.

Super-resolution GANs can be used to enhance the resolution of images or videos.

Data augmentation GANs can be used to generate additional training data for other machine learning models.

Medical image analysis GANs have been used to generate synthetic medical images for tasks such as segmentation and classification.

Domain adaptation GANs can be used to translate images from one domain (*e.g., synthetic images*) to another domain (*e.g., real images*) to improve the performance of machine learning models.

GAN

CODE SNIPPET



Code is available at <https://github.com/a-mhamdi/jlai/>

→ Codes → Julia → Part-3 → *gan.jl*



Variational Autoencoder

VAE

MOTIVATING FACTORS

- ▶ A **Variational Autoencoder (VAE)** is a type of deep learning model that is used to learn latent representations of data. It is a generative model, which means that it can generate new samples of data that are similar to the training data.
- ▶ **VAEs** are trained to encode the data into a low-dimensional latent space and then decode the latent representation back into the original data space. During training, the **VAE** learns to reconstruct the input data, while also trying to enforce a constraint on the latent space that encourages it to represent the data in a meaningful way.
- ▶ The constraint that is used in a **VAE** is called the variational lower bound. This lower bound is maximized during training, which encourages the latent space to be structured in a way that is useful for generating samples that are similar to the training data.

VAE

APPLICATIONS

Generative modeling VAEs can be used to generate new samples of data that are similar to the training data. This can be useful for tasks such as image generation, audio synthesis, and natural language generation.

Anomaly detection VAEs can be used to identify anomalies in data by reconstructing the input data and measuring the reconstruction error. Data points that are poorly reconstructed are likely to be anomalous.

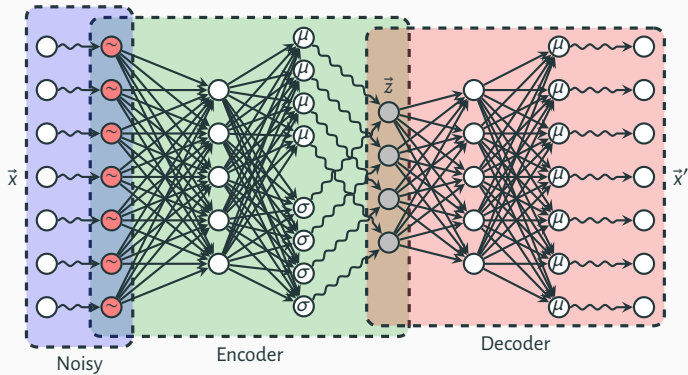
Data compression VAEs can be used to compress data by encoding it into a lower-dimensional latent space and then reconstructing it. The encoder can be used as a compression function, and the decoder can be used as a decompression function.

Representation learning VAEs can be used to learn meaningful latent representations of data, which can be useful for tasks such as clustering and classification.

Semi-supervised learning VAEs can be used in a semi-supervised setting, where only a small portion of the data is labeled. The VAE can use the labeled data to learn a meaningful latent representation of the data, and then use this representation to make predictions on the unlabeled data.

VAE

ARCHITECTURE



VAE

CODE SNIPPET



Code is available at <https://github.com/a-mhamdi/jlai/>

→ Codes → Julia → Part-3 → vae.jl



Natural Language Processing

NLP

PURPOSE OF NLP

- ▶ **Natural Language Processing (NLP)** is a field of artificial intelligence and computer science that focuses on the interaction between computers and humans using natural language.
- ▶ **NLP** involves the development of algorithms and models that can understand, interpret, and generate human language.
- ▶ **NLP** is used in a wide range of applications, including machine translation, question answering, text summarization, text classification, and sentiment analysis.

NLP

APPLICATIONS

Part-of-speech tagging Identifying the parts of speech (*e.g., noun, verb, adjective*) in a sentence

Named entity recognition Identifying and labeling named entities (*e.g., people, organizations, locations*) in a text

Sentiment analysis Determining the sentiment (*e.g., positive, neutral, negative*) of a piece of text

Machine translation Translating text from one language to another

Text summarization Generating a concise summary of a longer piece of text

NLP

GENERAL PROCESS IN JULIA

1. Preprocess the text data by lowercasing, removing punctuation, and splitting the text into individual tokens (*e.g.*, words or subwords).
2. Build a vocabulary of the most common tokens in the text data.
3. Encode the text data as a sequence of integers using the vocabulary.
4. Pad the encoded sequences to the same length to make them suitable for input to a model.
5. Define the **NLP** model using a library such as `Flux.jl` or `Knet.jl`.
6. Train the model using gradient descent and a suitable loss function.
7. Use the trained model to make predictions on new data.



Code is available at <https://github.com/a-mhamdi/jlai/>

→ *Codes* → *Julia* → *Part-3* → *nlp.jl*



Transfer Learning

TRANSFER LEARNING

DRIVING FORCES

- ▶ **Transfer Learning** is a machine learning technique in which a model that has been trained on one task is re-purposed on a second related task. **Transfer Learning** can be used to improve the performance of the second task by leveraging the knowledge learned from the first task.
- ▶ One common use of **Transfer Learning** is to fine-tune a pre-trained model on a new dataset. For example, a pre-trained image classification model that has been trained on a large dataset such as ImageNet can be fine-tuned on a smaller dataset of a different but related task, such as detecting objects in medical images. Fine-tuning the pre-trained model on the new dataset can lead to improved performance compared to training a model from scratch on the smaller dataset.
- ▶ **Transfer Learning** is useful because it allows a machine learning model to learn from a large amount of data, even if the data is not directly related to the task at hand. It can also be used to speed up the training process, since the model does not need to be trained from scratch.

TRANSFER LEARNING

APPLICATIONS

Image classification Transfer Learning has been used to fine-tune pre-trained image classification models on new datasets, such as identifying plant species from images of leaves or detecting objects in medical images.

Natural language processing Transfer Learning has been used to fine-tune pre-trained language models on new tasks, such as sentiment analysis or text classification.

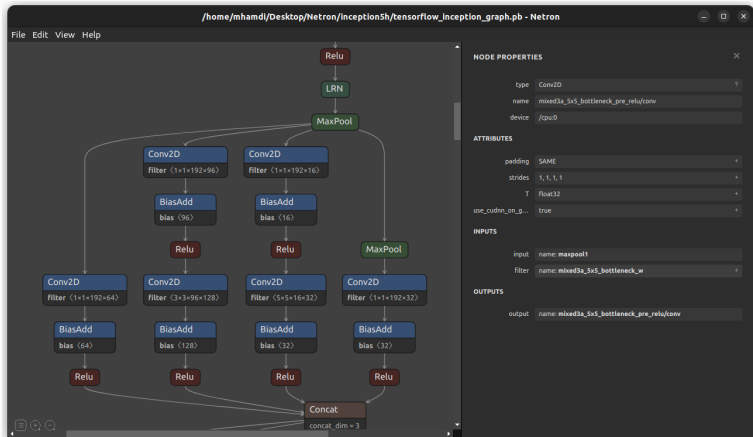
Speech recognition Transfer Learning has been used to fine-tune pre-trained speech recognition models on new languages or accents.

Computer vision Transfer Learning has been used to fine-tune pre-trained models for tasks such as object detection and image segmentation.

Robotics Transfer Learning has been used to fine-tune pre-trained models for tasks such as grasping objects or navigating a new environment.

TRANSFER LEARNING

NETRON



<https://github.com/lutzroeder/netron>

TRANSFER LEARNING

GENERAL PROCESS IN JULIA

1. Load the pre-trained model (*e.g.*, a convolutional neural network trained on ImageNet).
2. Replace the final layer (or layers) of the pre-trained model with a new, untrained layer (or layers) that is suitable for your target task.
3. Freeze the weights of the pre-trained layers to prevent them from being updated during training.
4. Load your dataset and split it into training and validation sets.
5. Use the training set to fine-tune the weights of the new layer (or layers) using gradient descent and a suitable loss function.
6. Monitor the performance of the model on the validation set and adjust the hyperparameters (*e.g.*, *learning rate*) as needed.
7. When you're satisfied with the performance of the model on the validation set, you can use it to make predictions on the test set or on new data.

TRANSFER LEARNING

CODE SNIPPET



Code is available at <https://github.com/a-mhamdi/jlai/>

→ Codes → Julia → Part-3 → *transfer-learning.jl*



Reinforcement Learning

REINFORCEMENT LEARNING

SYNOPSIS

- ▶ **Reinforcement Learning** is a type of machine learning in which an agent learns to interact with its environment in order to maximize a reward. It involves learning to map situations (called states) to actions that will maximize a reward. The agent receives feedback in the form of rewards and penalties for its actions, which it uses to adjust its behavior accordingly.
- ▶ In **reinforcement Learning**, the goal is to learn a policy that maximizes the cumulative reward over time. The agent learns this policy through **trial and error**, by exploring different actions in different states and receiving feedback in the form of rewards or penalties.
- ▶ **Reinforcement Learning** is used in a variety of applications, including control systems, game playing, and natural language processing. It has been successful in a number of tasks, including teaching a computer to play chess and Go at a high level.

REINFORCEMENT LEARNING

CODE SNIPPET



Code is available at <https://github.com/a-mhamdi/jlai/>

→ Codes → Julia → Part-3 → reinforcement-learning.jl



Quizzes

MCQ (1/1)

1. Your supervisor asks you to create a machine learning system that will help your human resources department classify jobs applicants into well-defined groups. What type of system are you more likely to recommend?
 - ✗ an unsupervised machine learning system that clusters together the best candidates.
 - ✗ you would not recommend a machine learning system for this type of project.
 - ✗ a deep learning artificial neural network that relies on petabytes of employment data.
 - ✓ a supervised machine learning system that classifies applicants into existing groups.
2. Your data science team must build a binary classifier, and the number one criterion is the fastest possible scoring at deployment. It may even be deployed in real time. Which technique will produce a model that will likely be fastest for the deployment team use to new cases?
 - ✗ random forest
 - ✓ logistic regression
 - ✗ KNN
 - ✗ deep neural network
3. The famous data scientist Andrew Ng has been quoted as saying, "Applied machine learning is basically feature engineering." What is feature engineering?
 - ✗ scraping new features from web data
 - ✓ creating new variables by combining and modifying the original variables
 - ✗ designing innovative new user features to add to software
 - ✗ using deep learning to find features in the data

SOME USEFUL LINKS

1. <https://setosa.io/ev/>
2. <https://karpathy.ai/>
3. <http://yann.lecun.com/>
4. <https://www.hackingnote.com/>
5. <https://machinelearningmastery.com/>
6. <https://stanford.edu/~shervine/teaching/>
7. <https://www.ibm.com/downloads/cas/GB8ZMQZ3>
8. <https://colah.github.io/posts/2014-03-NN-Manifolds-Topology/>

FURTHER READING (1/2)

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