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EMERGING TRENDS OF DEEP LEARNING APPROACH OF ARTIFICIAL NEURAL NETWORK USING IMAGE CLASSIFIER METHOD IN PYTHON

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Abstract

Deep learning is a branch of machine learning which is based on artificial neural networks. It is capable of learning complex patterns and relationships within data. In deep learning, we don't need to explicitly program everything. It has become increasingly popular in recent years due to the advances in processing power and the availability of large datasets. Because it is based on artificial neural networks (ANNs) also known as deep neural networks (DNNs). These neural networks are inspired by the structure and function of the human brain's biological neurons, and they are designed to learn from large amounts of data. In summary, Deep Learning is a subfield of Machine Learning that involves the use of deep neural networks to model and solve complex problems. Deep Learning has achieved significant success in various fields, and its use is expected to continue to grow as more data becomes available, and more powerful computing resources become available.

Keywords: Deep Learning, Artificial Neural Network, Image Classifier, Python

1. Introduction

Deep learning is a specific subfield of machine learning: a new take on learning representations from data that puts an emphasis on learning successive layers of increasingly meaningful representations. The deep in deep learning isn't a reference to any kind of deeper understanding achieved by the approach; rather, it stands for this idea of successive layers of representations. How many layers contribute to a model of the data is called the depth of the model. Other appropriate names for the field could have been layered representations learning and hierarchical representations learning. Modern deep learning often involves tens or even hundreds of successive layers of representations— and they're all learned automatically from exposure to training data. Meanwhile, other approaches to machine learning tend to focus on learning only one or two layers of representations of the data; hence, they're sometimes called shallow learning. In deep learning, these layered representations are (almost always) learned via models called neural networks, structured in literal layers stacked on top of each other. The term neural network is a reference to neurobiology, but although some of the central concepts in deep learning were developed in part by drawing inspiration from our understanding of the brain, deep-learning models are not models of the brain. There's no evidence that the brain implements anything like the learning mechanisms used in modern deep-learning models. You may come across pop-science articles proclaiming that deep learning works like the brain or was modeled after the brain, but that isn't the case. It would be confusing and counterproductive for newcomers to the field to think of deep learning as being in any way related to neurobiology; you don't need that shroud of "just like our minds" mystique and mystery, and you may as well forget anything you may have read about hypothetical links between deep learning and biology. For our purposes, deep learning is a mathematical framework for learning representations from data.

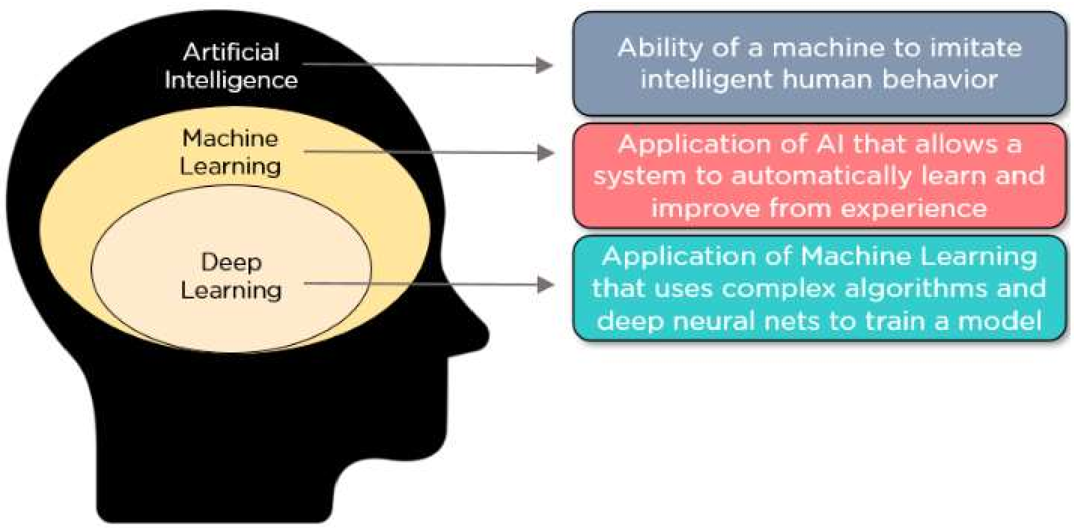

Fig 1 Processing between AI, ML and Deep Learning

1. 2. A BRIEF HISTORY OF DEEP LEARNING

Deep Learning, is a more evolved branch of machine learning, and uses layers of algorithms to process data, and imitate the thinking process, or to develop *abstractions*.

It is often used to visually recognize objects and understand human speech. Information is passed through each layer, with the output of the previous layer providing input for the next layer. The first layer in a network is called the input layer, while the last is called an output layer.

All the layers between input and output are referred to as hidden layers. Each layer is typically a simple, uniform algorithm containing one kind of activation function.

Feature extraction is another aspect of deep learning. It is used for pattern recognition and image processing. Feature extraction uses an algorithm to automatically construct meaningful "features" of the data for purposes of training, learning, and understanding. Normally a data scientist, or a programmer, is responsible for feature extraction.

The history of deep learning can be traced back to 1943, when Walter Pitts and Warren McCulloch created a computer model based on the neural networks of the human brain.

They used a combination of algorithms and mathematics they called "threshold logic" to mimic the thought process. Since that time, Deep Learning has evolved steadily, with only two significant breaks in its development. Both were tied to the infamous Artificial Intelligence winters

2.1 The 1960s

Henry J. Kelley is given credit for developing the basics of a continuous Back Propagation Modelin 1960. In 1962, a simpler version based only on the chain rule was developed by Stuart Dreyfus. While the concept of back propagation (the backward propagation of errors for purposes of training) did exist in the early 1960s, it was clumsy and inefficient, and would not become useful until 1985.

2.2 The 1970s

During the 1970's the first AI winter kicked in, the result of promises that couldn't be kept. The impact of this lack of funding limited both DL and AI research. Fortunately, there were individuals who carried on the research without funding.

2.3 The 1980s and 90s

In 1989, Yann LeCun provided the first practical demonstration of back propagation at Bell Labs. He combined convolutional neural networks with back propagation onto read "handwritten" digits. This system was eventually used to read the numbers of handwritten checks.

2.4 2000-2010

Around the year 2000, The Vanishing Gradient Problem appeared. It was discovered "features" (lessons) formed in lower layers were not being learned by the upper layers, because no learning signal reached these layers. This was not a fundamental problem for all neural networks, just the ones with gradient-based learning methods. The source of the problem turned out to be certain activation functions. A number of activation functions condensed their input, in turn reducing the output range in a somewhat chaotic fashion. This produced large areas of input mapped over an extremely small range. In these areas of input, a large change will be reduced to a small change in the output, resulting in a vanishing gradient. Two solutions used to solve this problem were layer-by-layer pre-training and the development of long short-term memory.

2.5 2011-2020

By 2011, the speed of GPUs had increased significantly, making it possible to train convolution neural networks "without" the layer-by-layer pre-training. With the increased computing speed, it became obvious deep learning had significant advantages in terms of efficiency and speed. One example is AlexNet, a convolution neural network whose architecture won several international competitions during 2011 and 2012. Rectified linear units were used to enhance the speed and dropout.

The Generative Adversarial Neural Network (GAN) was introduced in 2014. GAN was created by Ian Good fellow. With GAN, two neural networks play against each other in a game. The goal of the game is for one network to imitate a photo, and trick its opponent into believing it is real. The opponent is, of course, looking for flaws. The game is played until the near perfect photo tricks the opponent. GAN provides a way to perfect a product (and has also begun being used by scammers).

3. Artificial Neural Networks

Artificial neural networks are built on the principles of the structure and operation of human neurons. It is also known as neural networks or neural nets. An artificial neural network's input layer, which is the first layer, receives input from external sources and passes it on to the hidden layer, which is the second layer. Each neuron in the hidden layer gets information from the neurons in the previous layer, computes the weighted total, and then transfers it to the neurons in the next layer. These connections are weighted, which means that the impacts of the inputs from this preceding layer are more or less optimized by giving each input a distinct weight. These weights are then adjusted during the training process to enhance the performance of the model.

2.

3.

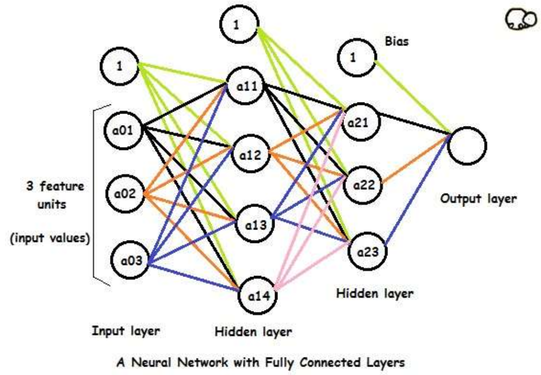

Fig 2. Fully Connected Artificial Neural Network

Artificial neurons, also known as units, are found in artificial neural networks. The whole Artificial Neural Network is composed of these artificial neurons, which are arranged in a series of layers. The complexities of neural networks will depend on the complexities of the underlying patterns in the dataset whether a layer has a dozen units or millions of units. Commonly, Artificial Neural Network has an input layer, an output layer as well as hidden layers. The input layer receives data from the outside world which the neural network needs to analyze or learn about.

In a fully connected artificial neural network, there is an input layer and one or more hidden layers connected one after the other. Each neuron receives input from the previous layer neurons or the input layer. The output of one neuron becomes the input to other neurons in the next layer of the network, and this process continues until the final layer produces the output of the network. Then, after passing through one or more hidden layers, this data is transformed into valuable data for the output layer. Finally, the output layer provides an output in the form of an artificial neural network's response to the data that comes in.

Units are linked to one another from one layer to another in the bulk of neural networks. Each of these links has weights that control how much one unit influences another. The neural network learns more and more about the data as it moves from one unit to another, ultimately producing an output from the output layer.

4. Types of neural networks

Deep Learning models are able to automatically learn features from the data, which makes them well-suited for tasks such as image recognition, speech recognition, and natural language processing. The most widely used architectures in deep learning are feed forward neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs).

Feedforward neural networks (FNNs) are the simplest type of ANN, with a linear flow of information through the network. FNNs have been widely used for tasks such as image classification, speech recognition, and natural language processing.

Convolution Neural Networks (CNNs) are specifically for image and video recognition tasks. CNNs are able to automatically learn features from the images, which makes them well-suited for tasks such as image classification, object detection, and image segmentation.

Recurrent Neural Networks (RNNs) are a type of neural network that is able to process sequential data, such as time series and natural language. RNNs are able to maintain an internal state that captures information about the previous inputs, which makes them well-suited for tasks such as speech recognition, natural language processing, and language translation.

5. Applications of Deep Learning

The main applications of deep learning can be divided into computer vision, natural language processing (NLP), and reinforcement learning.

5.1 Computer vision

In computer vision, Deep learning models can enable machines to identify and understand visual data. Some of the main applications of deep learning in computer vision include:

5.2 Object detection and recognition: Deep learning model can be used to identify and locate objects within images and videos, making it possible for machines to perform tasks such as self-driving cars, surveillance, and robotics.

5.3 Image classification: Deep learning models can be used to classify images into categories such as animals, plants, and buildings. This is used in applications such as medical imaging, quality control, and image retrieval.

5.4 Image segmentation: Deep learning models can be used for image segmentation into different regions, making it possible to identify specific features within images.

6. Natural language processing (NLP)

In NLP, the Deep learning model can enable machines to understand and generate human language. Some of the main applications of deep learning in NLP include:

6.1 Automatic Text Generation – Deep learning model can learn the corpus of text and new text like summaries, essays can be automatically generated using these trained models.

6.2 Language translation: Deep learning models can translate text from one language to another, making it possible to communicate with people from different linguistic backgrounds.

7. Reinforcement learning:

In reinforcement learning, deep learning works as training agents to take action in an environment to maximize a reward. Some of the main applications of deep learning in reinforcement learning include:

7.1 Game playing: Deep reinforcement learning models have been able to beat human experts at games such as Go, Chess, and Atari.

7.2 Robotics: Deep reinforcement learning models can be used to train robots to perform complex tasks such as grasping objects, navigation, and manipulation.

7.3 Control systems: Deep reinforcement learning models can be used to control complex systems such as power grids, traffic management, and supply chain optimization.

7.4 Sentiment analysis: Deep learning models can analyze the sentiment of a piece of text, making it possible to determine whether the text is positive, negative, or neutral. This is used in applications such as customer service, social media monitoring, and political analysis.

7.5 Speech recognition: Deep learning models can recognize and transcribe spoken words, making it possible to perform tasks such as speech-to-text conversion, voice search, and voice-controlled devices.

8. Challenges in Deep Learning

Deep learning has made significant advancements in various fields, but there are still some challenges that need to be addressed. Here are some of the main challenges in deep learning:

Data availability: It requires large amounts of data to learn from. For using deep learning it’s a big concern to gather as much data for training.

Computational Resources: For training the deep learning model, it is computationally expensive because it requires specialized hardware like GPUs and TPUs.

Time-consuming: While working on sequential data depending on the computational resource it can take very large even in days or months.

Interpretability: Deep learning models are complex, it works like a black box. it is very difficult to interpret the result.

Overfitting: when the model is trained again and again, it becomes too specialized for the training data, leading to overfitting and poor performance on new data.

9. Conclusion and Future Scope

Deep learning has provided image-based product searches – Ebay, Etsy– and efficient ways to inspect products on the assembly line. The first supports consumer convenience, while the second is an example of business productivity.

Currently, the evolution of artificial intelligenceis dependent on deep learning. Deep learning is still evolving and in need of creative ideas.

Semantics technology is being used with deep learning to take artificial intelligence to the next level, providing more natural sounding, human-like conversations.

Deep learning and artificial intelligence are influencing the creation of new business models. These businesses are creating new corporate cultures that embrace deep learning, artificial intelligence, and modern technology.

4. 10. DEEP LEARNING APPROACH USING PYTHON

A few basic applications of machine learning have been explored and implemented with respect to this research using python programming language. The names of the application is as follows:

11. Image Classifier

Implementation using Python Scikit-learn library was used for importing the required model. The labeled training data was manipulated, resized,reshaped and transposed using PIL and NumPy. This image data was then converted into an array using KERAS library. The model was trained over this data. In order to classify the image given by the user, it was first manipulated, resized, reshaped and transposed and converted to an array of same size as training data then further the category of given image was predicted by the model.

- Model Used: Multi-Layer Perceptron (MLP Classifier) from scikit-learn
- Code Snippet:

```
dpath= r'E:\Research\IC-18\cat-and-
dog\training_set\dogs'cpath= r'E:\Research\IC-18\cat-
and-dog\training_set\cats' def convert(path):
  labe
  l =
  []ad
  = []
  c=0
  for file in os.listdir(path):
    label.append(file.split('.')[0])
    f=os.path.join(path,file)
    im= Image.open(f)
    im=
    im.convert(mode='RGB')
    imrs=
    im.resize((100,100))
    imrs=
    img_to_array(imrs)/255
    #imrs.transpose((2, 0, 3,
    1)).reshape(4,4)imrs=
    imrs.reshape(100*100*3)
    ad.append(imrs)
    c+=1
  print("do
  ne")
  return
  ad,label

mlp= MLPClassifier (activation= 'logistic', solver=
'sgd')cat_data,cat_label = convert(cpath)
dog_data,dog_label = convert(dpath)
main_data =
cat_data+dog_data main_label
= cat_label+dog_label
main_data =
np.asarray(main_data)
main_label =
np.asarray(main_label)
```

```
main_label=
main_label.reshape(len(main_label), -1)
print(main_data.shape)
print("started")

mlp.fit(main_data,

main_label)

t_data = []
t = r'E:\Research\IC-18\cat-and-
dog\test_set\cats\cat.4001.jpg'te = Image.open(t)
tes =
te.convert(mode="RGB")
test =
tes.resize((100,100)) test
=
img_to_array(test)/255
ta = test
testa =
test.reshape(3*100*100)
t_data.append(testa)

t_data =
np.asarray(t_data)
pred=
mlp.predict(t_data)
image =
mpimg.imread(t)
print(pred)
tr= ("classified as: {}".
format(str(pred[0])))plt.text (15, 35, tr,
fontsize=15) plt.imshow(image)
plt.show()
```

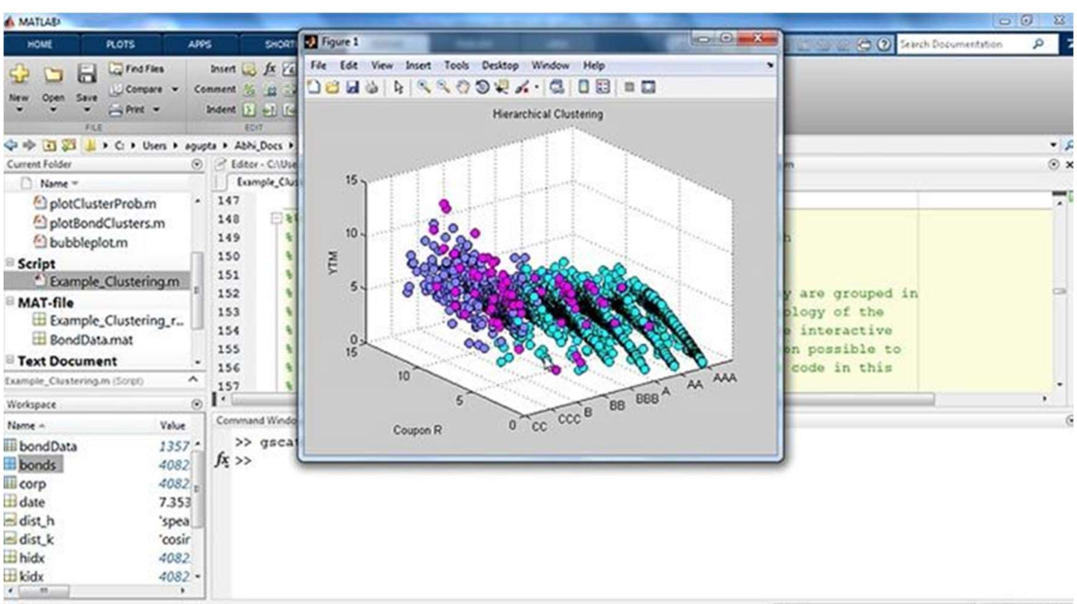

Fig 3 Example of Image Classifier

Fig 4. Image Classifier of Plants

- Interpretation: The dataset containing around 8000 images of cats and dogs was used to train the image classifier model and for testing a separate dataset was used containing approximately 2000 images of cats and dogs. The model was executed three times during testing with different image paths. The results show that the model was fairly able to recognize cats and dogs separately. If the size of dataset was reduced, as an experiment by the researchers, the accuracy of the model was affected in a negative way.

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