Summary Report 2 on ML Course

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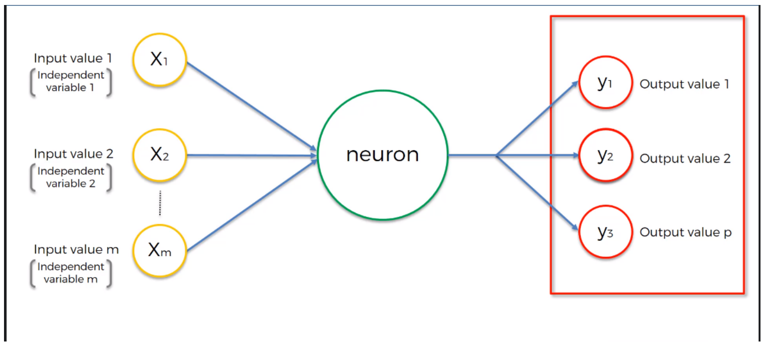
1 Artificial Neural Networks (ANN)

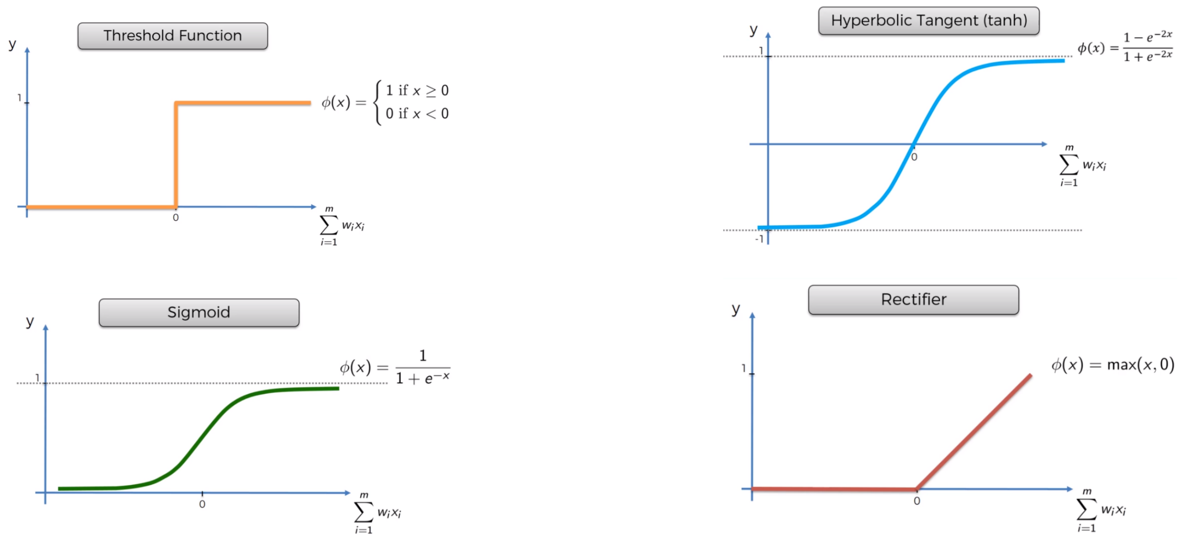
1.1 Introduction

Artificial neural networks (ANNs) are a powerful class of machine learning algorithms that are modeled after the structure and function of the human brain. ANNs are capable of learning complex patterns and relationships in data and are used in a wide range of applications, from image and speech recognition to natural language processing and predictive modeling. ANNs are made up of interconnected nodes or neurons that process and transmit information through a network of layers. As the network processes data, it adjusts the weights and biases of the connections between neurons to improve its accuracy and predictive power. In this way, ANNs are able to learn from data and improve their performance over time.



1.2 Activation Function

Activation functions are mathematical functions that are applied to the output of each neuron in an artificial neural network (ANN). They introduce non-linearity into the network, allowing it to model complex patterns and relationships in data. Common activation functions include the sigmoid function, the rectified linear unit (ReLU) function, and the hyperbolic tangent (tanh) function. The choice of activation function can have a significant impact on the performance of the network, and different activation functions may be more appropriate for different types of data and tasks.

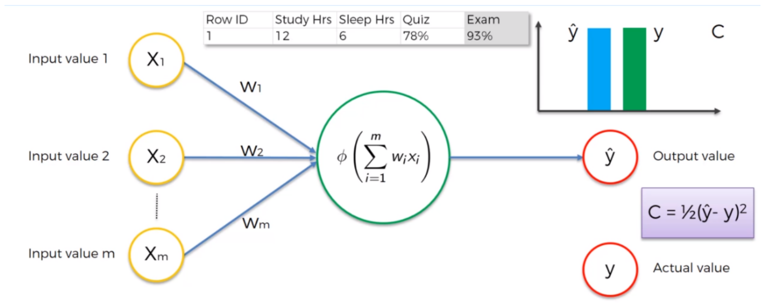


1.3 How Do Neural Networks Work?

They are composed of layers of interconnected nodes that process and analyze data, gradually learning and improving their accuracy over time. When presented with input data, the first layer of a neural network receives the raw data and passes it through a series of mathematical functions that transform it into more abstract representations. These representations are then fed to subsequent layers, which continue to refine and process the data until a final output is produced. Through a process of trial and error, neural networks learn to adjust the weights and biases of each node to minimize errors and improve their predictions.

1.4 How Do Neural Networks Learn?

Neural networks learn through a process called backpropagation, which involves minimizing the cost or error function of the network. During training, the network is presented with a set of labeled training examples, and the weights and biases of each node are adjusted to minimize the difference between the predicted output and the actual output. This difference is calculated using a cost or loss function, which measures the discrepancy between the predicted output and the actual output. The network then uses an optimization algorithm such as gradient descent to iteratively adjust the weights and biases of each node to minimize the cost function. This process of adjusting the weights and biases based on the cost function is repeated many times, gradually improving the accuracy and performance of the network. By minimizing the cost function, neural networks can learn to make accurate predictions and classify new data with high accuracy.



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1	12	6	78%	93%

2 Convolutional Neural Networks

2.1 What are Convolutional Neural Networks?

In recent years, there has been an explosion of interest and research in the field of artificial intelligence (AI) and machine learning. One of the most powerful tools in this field is the Convolutional Neural Network (CNN), which has revolutionized the field of computer vision and image processing.

A CNN is a type of neural network that is designed specifically for processing data that has a grid-like structure, such as images. The network consists of multiple layers, each of which performs a different type of operation on the input data.

The first layer of a CNN is typically a convolutional layer, which applies a set of filters to the input image. These filters are designed to detect specific features in the image, such as edges or corners. The output of the convolutional layer is a set of feature maps, which represent the presence or absence of these features in different parts of the image.

The next layer of the CNN is typically a pooling layer, which reduces the dimensionality of the feature maps by downsampling them. This helps to make the network more efficient and reduces the risk of overfitting.

The final layer of the CNN is typically a fully connected layer, which takes the output of the previous layer and maps it to a set of output classes. This layer uses the information from the previous layers to make a prediction about the input image.

One of the key advantages of CNNs is their ability to learn hierarchical representations of the input data. By stacking multiple convolutional and pooling layers on top of each other, the network is able to learn increasingly complex representations of the input image, which can be used to make more accurate predictions.

Another advantage of CNNs is their ability to perform data augmentation. This involves applying various transformations to the input data, such as flipping or rotating the image, in order to create additional training examples. This helps to prevent overfitting and improves the generalization performance of the network.

In conclusion, Convolutional Neural Networks are a powerful tool in the field of machine learning, specifically for image processing and computer vision. They are designed to learn hierarchical representations of grid-like input data such as images, and have shown tremendous success in various applications including object recognition, image classification, and more.

2.2 Convolution and Feature Maps in Convolutional Neural Networks

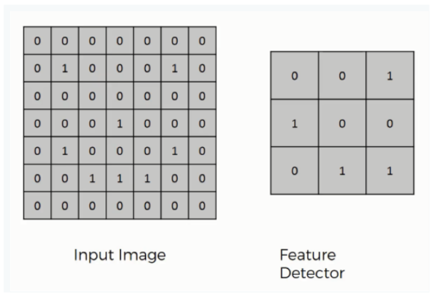
Convolution is the first step in a Convolutional Neural Network (CNN), where the input data, usually an image, is convolved with a set of learnable filters called feature detectors or kernels. The result is a set of feature maps that highlight the presence or absence of specific features in different parts of the image.

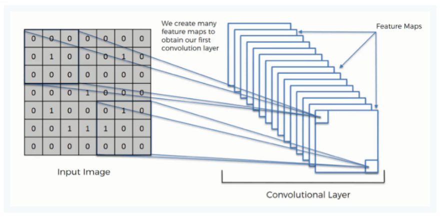
These feature maps are the input to the next layer of the CNN, where the network learns increasingly complex features and hierarchical representations of the input data. The size and number of feature maps generated by a convolutional layer depends on factors such as the size of the input image, the number and size of feature detectors, and the stride and padding used during the convolution operation.

By updating the weights of the network using backpropagation during training, the network learns to optimize its feature detectors to detect the most useful and relevant features for a given task, such as object recognition or image classification.

In summary, convolution and feature maps are key concepts in CNNs, allowing the network to learn and represent increasingly complex features of the input data, leading to improved performance on a range of computer vision tasks.

The Convolution Operation




We create many feature maps to obtain our first convolution layer
Feature Maps
Input Image
Convolutional Layer

2.3 ReLU Layer in Convolutional Neural Networks

Rectified Linear Unit (ReLU) is a popular activation function used in Convolutional Neural Networks (CNNs) that can help improve the network's performance. ReLU is applied as a layer in the CNN, following the convolutional layer.

The ReLU layer is a non-linear activation function that replaces all negative values in the feature maps with zero, while leaving positive values unchanged. This results in an output that is always non-negative and helps to introduce non-linearity into the network, which is crucial for learning complex patterns in the input data.

The ReLU function is simple, computationally efficient, and has been shown to improve the convergence of the network during training. It also helps to alleviate the vanishing gradient problem that can occur in deeper networks, where the gradient of the activation function approaches zero, making it difficult to update the weights of the earlier layers in the network.

The ReLU layer can be implemented using hardware accelerators, making it a popular choice for deep learning applications that require real-time processing, such as in self-driving cars or robotics.

Despite its advantages, ReLU has some limitations. One of the main drawbacks is the possibility of "dying ReLU" or the "ReLU death" problem, where a neuron can become permanently inactive during training and never recover. This can result in a loss of representational power and slower convergence during training.

To mitigate this problem, various modifications to the ReLU function have been proposed, such as leaky ReLU, which introduces a small non-zero slope for negative values, or exponential linear units (ELUs), which introduce a small negative slope for negative values. These modifications can help to overcome the drawbacks of the original ReLU function while retaining its benefits.

In conclusion, the ReLU layer is a popular activation function used in CNNs to introduce non-linearity and improve the performance of the network. While it has some limitations, modifications to the original function have been proposed to overcome these problems and make it a powerful tool for deep learning applications.

2.4 Pooling in Convolutional Neural Networks

Pooling is a technique used in Convolutional Neural Networks (CNNs) to reduce the dimensionality of feature maps generated by the convolutional layers. Pooling is usually applied after the ReLU layer and before the next convolutional layer in the CNN.

Pooling involves taking a small window or kernel over the feature map and summarizing the values within that window. There are several types of pooling techniques, including max pooling, average pooling, and min pooling.

The main purpose of pooling is to reduce the spatial size of the feature maps, making the network more computationally efficient and reducing the risk of overfitting. By summarizing the values within each window, the network can retain the most important information while discarding unnecessary details that may be less relevant for the task at hand.

Max pooling is a type of pooling technique that selects the maximum value within each window. This means that the output of the max pooling operation will be the maximum value within each window, effectively summarizing the most important information within that region.

Max pooling has several advantages. It helps to reduce the spatial size of the feature maps while retaining the most important features, making the network more computationally efficient and reducing the risk of overfitting. Additionally, max pooling can help to introduce translation invariance into the network, meaning that the network can recognize the same features in different parts of the image.

However, max pooling also has some limitations. One drawback is that it can lead to a loss of spatial information, since only the maximum value within each window is retained. This can make it difficult for the network to recognize fine details or localize objects precisely. Additionally, max pooling can introduce some amount of distortion, since it selects only one value within each window and discards the rest.

In summary, pooling is a technique used in CNNs to reduce the dimensionality of feature maps and make the network more computationally efficient. Max pooling is a popular type of pooling that selects the maximum value within each window and helps to retain the most important features while introducing translation invariance. However, max pooling also has some limitations, such as a loss of spatial information and potential distortion, which should be taken into account when designing a CNN architecture.

2.5 Flattening in CNN

Flattening is a process that is typically applied after the convolutional and pooling layers in a CNN. The output of these layers is a 3D tensor, where the first two dimensions represent the spatial dimensions of the feature map and the third dimension represents the number of channels or filters.

Flattening involves reshaping this 3D tensor into a 1D vector, which can then be used as input to a fully connected layer. This process essentially takes all the features learned by the convolutional and pooling layers and flattens them into a single long vector.

The purpose of flattening is to prepare the data for the fully connected layers, which require a 1D input vector. This step is necessary because fully connected layers cannot handle 3D tensors as input.

Overall, flattening is an important step in the CNN architecture, as it allows the network to utilize the features learned by the convolutional and pooling layers and use them to make predictions or classifications.

2.6 Fully Connected Layers in Convolutional Neural Networks

Fully connected layers, also known as dense layers, are a key component in convolutional neural networks (CNNs). They are typically placed at the end of a CNN architecture and are responsible for generating the final output of the network. In this chapter, we will discuss fully connected layers in detail, including their architecture, function, and role in CNNs.

2.6.1 Architecture of Fully Connected Layers

A fully connected layer consists of a set of neurons, where each neuron is connected to every neuron in the previous layer. The output of a fully connected layer is a one-dimensional array, where each element in the array represents the activation of a single neuron in the layer. The architecture of a fully connected layer can be represented by the following equation:

output = activation$_function(dot(input, weights) + bias)$

Where dot represents the dot product between the input and the weights of the layer, and bias is an optional constant value that is added to the output.

2.6.2 Function of Fully Connected Layers

The main function of fully connected layers is to perform classification and prediction tasks based on the features extracted by the convolutional layers in a CNN. These layers take the flattened output from the previous convolutional layers as input and generate a final output in the form of a probability distribution over the different classes.

The output of a fully connected layer can be further processed by a softmax activation function to obtain a normalized probability distribution. This distribution represents the network's predicted probability for each class label, which can be used to make a final prediction.

2.6.3 Role of Fully Connected Layers in CNNs

Fully connected layers play a crucial role in CNNs by enabling the network to learn complex representations of input data. The convolutional layers extract spatial features from the input images, while the fully connected layers learn to classify these features into different categories.

The use of fully connected layers in CNNs has been shown to significantly improve the accuracy of image classification and recognition tasks. However, it is important to note that the number of fully connected layers and their size can have a significant impact on the performance of the network.

2.6.4 Summary

Fully connected layers are a key component in CNNs and are responsible for generating the final output of the network. They perform classification and prediction tasks based on the features extracted by the convolutional layers, enabling the network to learn complex representations of input data. The use of fully connected layers has been shown to significantly improve the accuracy of image recognition tasks and is an important area of research in the field of deep learning.