

STAR LION COLLEGE OF ENGINEERING AND TECHNOLOGY

Date	18/10/2023
Name	K.Anushiya
Department	Computer Science And Engineering
Project	Create A Chatbot In Python
Register number	822021104002
Naan mudhalvan ID	au822021104002

Create A Chatbot In Python

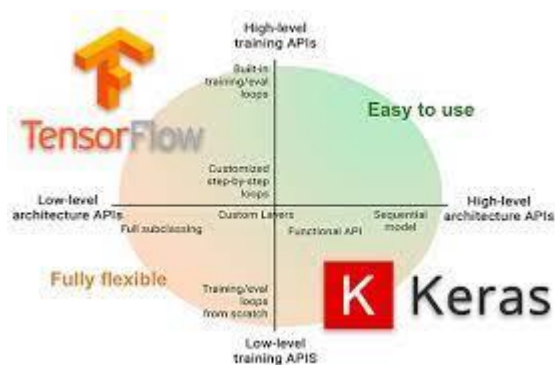
Phase -3 Submission Document

Project:Create A chatbot In Python

Tensorflow & keras-ANN: we are going to see some basics of ANN and a simple implementation of an artificial neural network. Tensorflow is a powerful machine learning library to create models and neural networks.

Pytorch Vs Tensorflow Vs Keras: The Differences You Should Know

TensorFlow is an open-sourced end-to-end platform, a library for multiple machine learning tasks, while Keras is a high-level neural network library that runs on top of TensorFlow. Both provide high-level APIs used for easily building and training models, but Keras is more user-friendly because it's built-in Python.



Keras: The high-level API for TensorFlow

Book mark _border

Keras is the high-level API of the TensorFlow platform. It provides an approachable, highly-productive interface for solving machine

learning (ML) problems, with a focus on modern deep learning. Keras covers every step of the machine learning workflow, from data processing to hyper parameter tuning to deployment. It was developed with a focus on enabling fast experimentation.

With Keras, you have full access to the scalability and cross-platform capabilities of TensorFlow. You can run Keras on a TPU Pod or large clusters of GPUs, and you can export Keras models to run in the browser or on mobile devices. You can also serve Keras models via a web API.

Keras is designed to reduce cognitive load by achieving the following goals:

- Offer simple, consistent interfaces.

- Minimize the number of actions required for common use cases.

- Provide clear, actionable error messages.

- Follow the principle of progressive disclosure of complexity: It's easy to get started, and you can complete advanced workflows by learning as you go.

- Help you write concise, readable code.

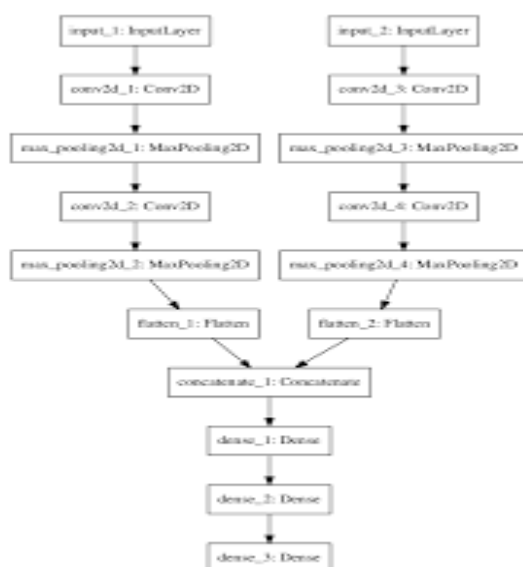
Who should use Keras

The short answer is that every TensorFlow user should use the Keras APIs by default. Whether you're an engineer, a researcher, or an ML practitioner, you should start with Keras.

There are a few use cases (for example, building tools on top of Tensor Flow or developing your own high-performance platform) that require the low-level Tensor Flow Core APIs. But if your use case doesn't fall into one of the Core API applications, you should prefer Keras.

Keras API components

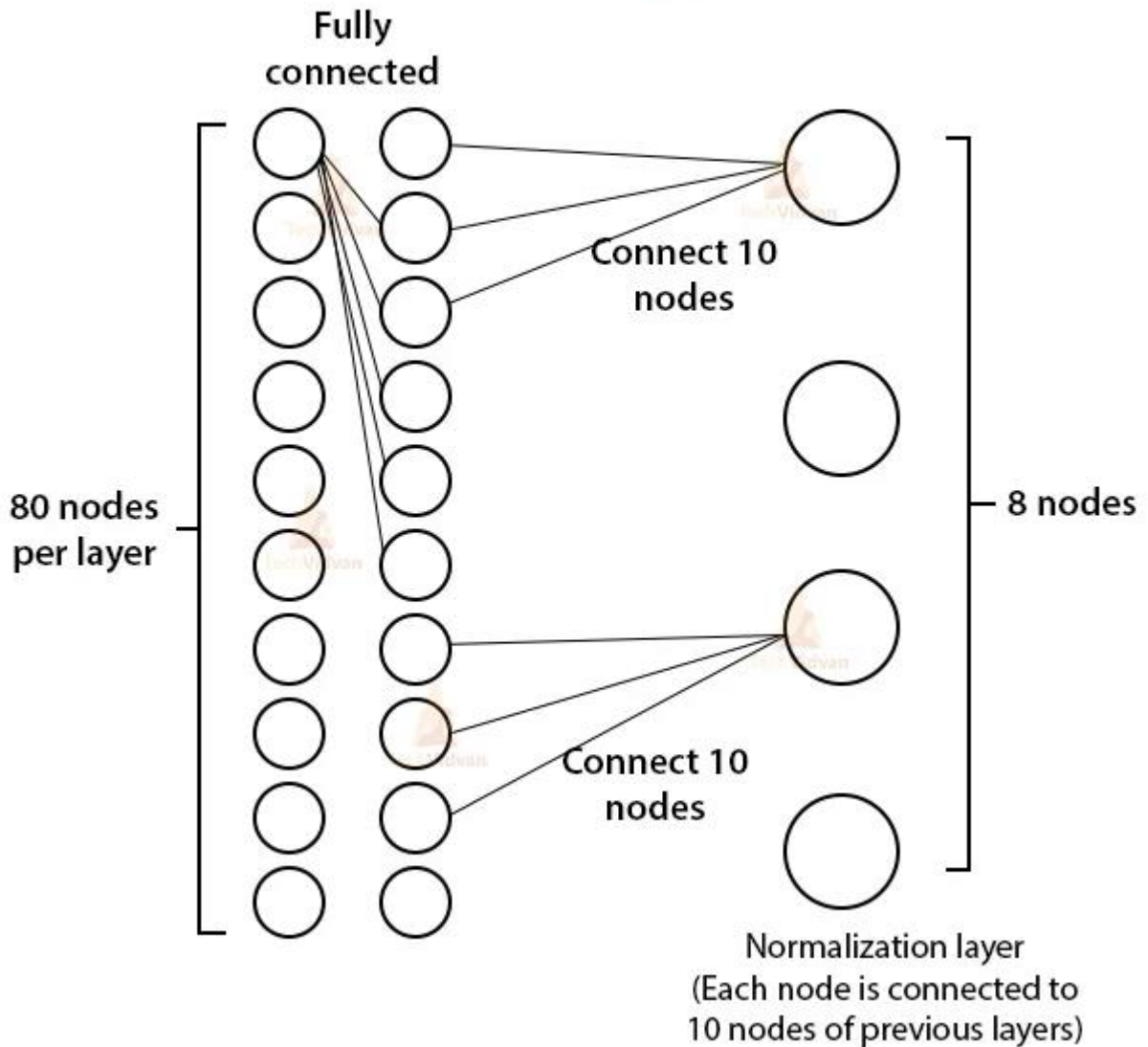
The core data structures of Keras are layers and models. A layer is a simple input/output transformation, and a model is a directed acyclic graph (DAG) of layers.



Layers

The `tf.keras.layers` Layer class is the fundamental abstraction in Keras. A Layer encapsulates a state (weights) and some computation (defined in the `tf.keras.layers.Layer.call` method).

Normalization Layer in Keras



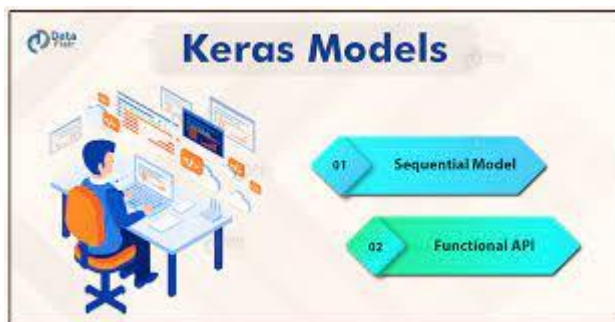
Weights created by layers can be trainable or non-trainable. Layers are recursively composable: If you assign a layer instance as an attribute of another layer, the outer layer will start tracking the weights created by the inner layer.

You can also use layers to handle data preprocessing tasks like normalization and text vectorization. Preprocessing layers can be

included directly into a model, either during or after training, which makes the model portable.

Models

A model is an object that groups layers together and that can be trained on data.



The simplest type of model is the Sequential model, which is a linear stack of layers. For more complex architectures, you can either use the Keras functional API, which lets you build arbitrary graphs of layers, or use subclassing to write models from scratch.

The `tf.keras.Model` class features built-in training and evaluation methods:

`tf.keras.Model.fit`: Trains the model for a fixed number of epochs.

`tf.keras.Model.predict`: Generates output predictions for the input samples.

`tf.keras.Model.evaluate`: Returns the loss and metrics values for the model; configured via the `tf.keras.Model.compile` method.

These methods give you access to the following built-in training features:

Callbacks. You can leverage built-in callbacks for early stopping, model check pointing, and Tensor Board monitoring. You can also implement custom callbacks.

Distributed training. You can easily scale up your training to multiple GPUs, TPUs, or devices.

Step fusing. With the `steps_per_execution` argument in `tf.keras.Model.compile`, you can process multiple batches in a single `tf.function` call, which greatly improves device utilization on TPUs.

For a detailed overview of how to use `fit`, see the training and evaluation guide. To learn how to customize the built-in training and evaluation loops, see [Customizing what happens in `fit\(\)`](#).

Other APIs and tools

Keras provides many other APIs and tools for deep learning, including:

Optimizers

Metrics

Losses

Data loading utilities

For a full list of available APIs, see the [Keras API reference](#). To learn more about other Keras projects and initiatives, see [The Keras ecosystem](#).

Next steps

To get started using Keras with TensorFlow, check out the following topics:

The Sequential model

The Functional API

Training & evaluation with the built-in methods

Making new layers and models via sub classing

Serialization and saving

Working with preprocessing layers

Customizing what happens in fit()

Writing a training loop from scratch

Working with RNNs

Understanding masking & padding

Writing your own callbacks

Transfer learning & fine-tuning

Multi-GPU and distributed training

To learn more about Keras, see the following topics at keras.io:

About Keras

Introduction to Keras for Engineers

Introduction to Keras for Researchers

Keras API reference

The Keras ecosystem

Convolutional neural network:

Neural networks are a subset of machine learning, and they are at the heart of deep learning algorithms. They are comprised of node layers, containing an input layer, one or more hidden layers, and an output layer. Each node connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network.

While we primarily focused on feedforward networks in that article, there are various types of neural nets, which are used for different use cases and data types. For example, recurrent neural networks are commonly used for natural language processing and speech recognition whereas convolutional neural networks (Conv Nets or CNNs) are more often utilized for classification and computer vision tasks. Prior to CNNs, manual, time-consuming feature extraction methods were used to identify objects in images. However, convolutional neural networks now provide a more scalable approach to image classification and object recognition tasks, leveraging principles from linear algebra, specifically matrix multiplication, to identify patterns within an image. That said, they can be computationally demanding, requiring graphical processing units (GPUs) to train m

What are convolutional neural networks?

Neural networks are a subset of machine learning, and they are at the heart of deep learning algorithms. They are comprised of node layers, containing an input layer, one or more hidden layers, and an output layer. Each node connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to

the next layer of the network. Otherwise, no data is passed along to the next layer of the network.

While we primarily focused on feedforward networks in that article, there are various types of neural nets, which are used for different use cases and data types. For example, recurrent neural networks are commonly used for natural language processing and speech recognition whereas convolutional neural networks (ConvNets or CNNs) are more often utilized for classification and computer vision tasks. Prior to CNNs, manual, time-consuming feature extraction methods were used to identify objects in images. However, convolutional neural networks now provide a more scalable approach to image classification and object recognition tasks, leveraging principles from linear algebra, specifically matrix multiplication, to identify patterns within an image. That said, they can be computationally demanding, requiring graphical processing units (GPUs) to train models.

Trial

Now available: watsonx.ai

The all new enterprise studio that brings together traditional machine learning along with new generative AI capabilities powered by foundation models.

Related content

Subscribe to the IBM newsletter

How do convolutional neural networks work?

Convolutional neural networks are distinguished from other neural networks by their superior performance with image, speech, or audio signal inputs. They have three main types of layers, which are:

Convolutional layer

Pooling layer

Fully-connected (FC) layer

The convolutional layer is the first layer of a convolutional network. While convolutional layers can be followed by additional convolutional layers or pooling layers, the fully-connected layer is the final layer. With each layer, the CNN increases in its complexity, identifying greater portions of the image. Earlier layers focus on simple features, such as colors and edges. As the image data progresses through the layers of the CNN, it starts to recognize larger elements or shapes of the object until it finally identifies the intended object.

Convolutional layer

The convolutional layer is the core building block of a CNN, and it is where the majority of computation occurs. It requires a few components, which are input data, a filter, and a feature map. Let's assume that the input will be a color image, which is made up of a matrix of pixels in 3D. This means that the input will have three dimensions—a height, width, and depth—which correspond to RGB in an image. We also have a feature detector, also known as a kernel or a filter, which will move across the receptive fields of the image, checking if the feature is present. This process is known as a convolution.

The feature detector is a two-dimensional (2-D) array of weights, which represents part of the image. While they can vary in size, the filter size is typically a 3x3 matrix; this also determines the size of the receptive field. The filter is then applied to an area of the image, and a dot product is calculated between the input pixels and the filter. This dot product is then fed into an output array. Afterwards, the filter shifts by a stride, repeating the process until the kernel has swept across the entire image. The final output from the series of dot products from the input and the filter is known as a feature map, activation map, or a convolved feature.

Note that the weights in the feature detector remain fixed as it moves across the image, which is also known as parameter sharing. Some parameters, like the weight values, adjust during training through the process of backpropagation and gradient descent. However, there are three hyper parameters which affect the volume size of the output that need to be set before the training of the neural network begins.

These include:

1. The number of filters affects the depth of the output. For example, three distinct filters would yield three different feature maps, creating a depth of three.
2. Stride is the distance, or number of pixels, that the kernel moves over the input matrix. While stride values of two or greater is rare, a larger stride yields a smaller output.
3. Zero-padding is usually used when the filters do not fit the input image. This sets all elements that fall outside of the input matrix to

zero, producing a larger or equally sized output. There are three types of padding:

Valid padding: This is also known as no padding. In this case, the last convolution is dropped if dimensions do not align.

Same padding: This padding ensures that the output layer has the same size as the input layer

Full padding: This type of padding increases the size of the output by adding zeros to the border of the input.

After each convolution operation, a CNN applies a Rectified Linear Unit (ReLU) transformation to the feature map, introducing nonlinearity to the model.

diagram a feature of detector

Additional convolutional layer

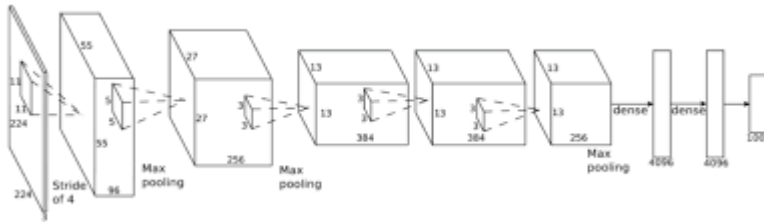
As we mentioned earlier, another convolution layer can follow the initial convolution layer. When this happens, the structure of the CNN can become hierarchical as the later layers can see the pixels within the receptive fields of prior layers. As an example, let's assume that we're trying to determine if an image contains a bicycle. You can think of the bicycle as a sum of parts. It is comprised of a frame, handlebars, wheels, pedals, et cetera. Each individual part of the bicycle makes up a lower-level pattern in the neural net, and the combination of its parts represents a higher-level pattern, creating a feature hierarchy within the CNN. Ultimately, the convolutional layer converts the image into numerical values, allowing the neural network to interpret and extract relevant patterns.



feature map

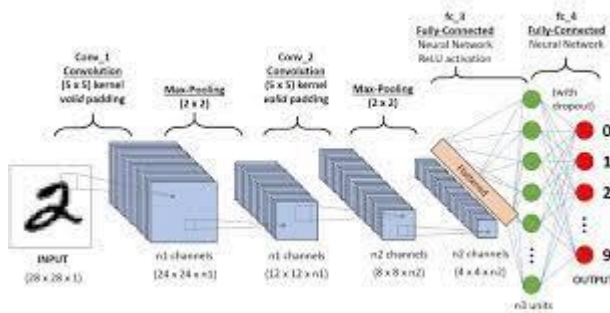
Pooling layer:

Pooling layers, also known as downsampling, conduct dimensionality reduction, reducing the number of parameters in the input. Similar to the convolutional layer, the pooling operation sweeps a filter across the entire input, but the difference is that this filter does not have any weights. Instead, the kernel applies an aggregation function to the values within the receptive field, populating the output array.

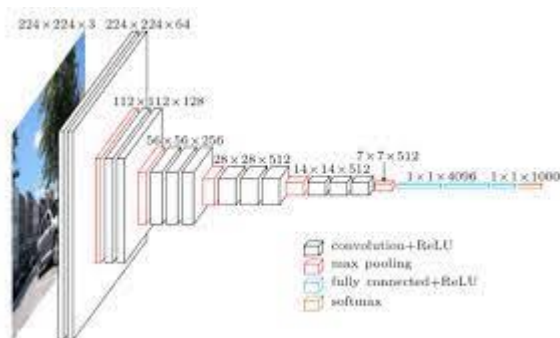


Max pooling: As the filter moves across the input, it selects the pixel with the maximum value to send to the output array. As an aside,

this approach tends to be used more often compared to average pooling.



Average pooling: As the filter moves across the input, it calculates the average value within the receptive field to send to the output array.



While a lot of information is lost in the pooling layer, it also has a number of benefits to the CNN. They help to reduce complexity, improve efficiency, and limit risk of overfitting.

Fully-connected layer

The name of the full-connected layer aptly describes itself. As mentioned earlier, the pixel values of the input image are not directly connected to the output layer in partially connected layers. However, in the fully-connected layer, each node in the output layer connects directly to a node in the previous layer.

This layer performs the task of classification based on the features extracted through the previous layers and their different filters. While convolutional and pooling layers tend to use Re Lu functions, FC layers usually leverage a soft max activation function to classify inputs appropriately, producing a probability from 0 to 1.

Types of convolutional neural networks:

Kuni hiko Fukushima and Yann Le Cun laid the foundation of research around convolutional neural networks in their work in 1980 ([link resides outside IBM](#)) and "Backpropagation Applied to Handwritten Zip Code Recognition" in 1989, respectively. More famously, Yann Le Cun successfully applied backpropagation to train neural networks to identify and recognize patterns within a series of handwritten zip codes. He would continue his research with his team throughout the 1990s, culminating with "LeNet-5", which applied the same principles of prior research to document recognition. Since then, a number of variant CNN architectures have emerged with the introduction of new datasets, such as MNIST and CIFAR-10, and competitions, like ImageNet Large Scale Visual Recognition Challenge (ILSVRC). Some of these other architectures include:

Alex Net ([link resides outside IBM](#))

VGG Net ([link resides outside IBM](#))

Google Net ([link resides outside IBM](#))

Res Net ([link resides outside IBM](#))

Open CU:

3 letter words made by unscrambling open cu

2 letter words made by unscrambling open cu

Word un scrambler for open cu

Words made by unscrambling letters open cu has returned 39 results. We have unscrambled the letters open cu using our word finder. We used letters of open cu to generate new words for Scrabble, Words With Friends, Text Twist, and many other word scramble games.

Our word scramble tool doesn't just work for these most popular word games though - these unscrambled words will work in hundreds of similar word games - including Boggle, Word le, Scrabble Go, Pic to word, Cryptogram, Spell Tower and many other word games that involve unscrambling words and finding word combinations!

