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Program 1

Train a Deep learning model to classify a given image using the pre-trained model.

Program:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, models, transforms
import numpy as np
from PIL import Image

# Define data transformations for preprocessing
data_transforms = {
    'train': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}

# Load a pre-trained ResNet-50 model
model = models.resnet50(pretrained=True)
num_features = model.fc.in_features

# Replace the final fully connected layer for binary classification
model.fc = nn.Linear(num_features, 2)

# Define a loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

# Load an image to classify
image_path = '/...../Path to Cat1.jpg'
image = Image.open(image_path)
image = data_transforms['train'](image)
image = image.unsqueeze(0)  # Add batch dimension

# Load the pre-trained model's weights
#model.load_state_dict(torch.load('/content/drive/MyDrive/20CSEL76-LAB Programs/resnet50-
0676ba61.pth'))

# Save the model state dictionary to a file
torch.save(model.state_dict(), 'resnet50_pretrained_weights.pth')
```

```
# Set the model to evaluation mode
model.eval()

# Make predictions
with torch.no_grad():
    outputs = model(image)
    _, predicted = torch.max(outputs, 1)

# Map class indices to class labels
class_labels = ['cat', 'dog']
predicted_class = class_labels[predicted.item()]

print(f'The image is classified as: {predicted_class}')
```

Output: The image is classified as: cat

Applications:

Translation, chatbots and other natural language processing applications

Program 2:

1. **Implement SVM/SoftMax classifier for the CIFAR-10 dataset:**
   a. **using KNN,**
   b. **using 3-layer neural network**

Program

Using KNN

```
# SVM Classifier for CIFAR-10 using scikit-learn (KNN)
import numpy as np
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier

# Load the CIFAR-10 dataset (You may need to download it separately)
# Load and preprocess the data
cifar10 = datasets.fetch_openml(name="CIFAR_10_small")
X = cifar10.data.astype('float32')
y = cifar10.target.astype('int')

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Create and train a K-Nearest Neighbors (KNN) classifier
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)

# Evaluate the classifier
accuracy = knn.score(X_test, y_test)
print(f"KNN Accuracy: {accuracy:.2f}")
```

Output: KNN Accuracy: 0.30

```
#Softmax Classifier for CIFAR-10 using PyTorch (3-layer neural network)
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import transforms, datasets
from torch.utils.data import DataLoader

# Set random seed for reproducibility
torch.manual_seed(42)

# Define a simple 3-layer neural network for Softmax classification
class SimpleNet(nn.Module):
    def __init__(self, input_size, num_classes):
        super(SimpleNet, self).__init__()
        self.fc1 = nn.Linear(input_size, 256)
        self.fc2 = nn.Linear(256, 128)
        self.fc3 = nn.Linear(128, num_classes)

    def forward(self, x):
        x = x.view(x.size(0), -1)  # Flatten the input
        x = torch.relu(self.fc1(x))
        x = torch.relu(self.fc2(x))
        x = self.fc3(x)
        return x

# Load and preprocess the CIFAR-10 dataset using torchvision
transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.5, 0.5, 0.5),
(0.5, 0.5, 0.5))])
cifar10_train = datasets.CIFAR10(root='./data', train=True, transform=transform,
download=True)
cifar10_test = datasets.CIFAR10(root='./data', train=False, transform=transform,
download=True)

# Set data loaders
train_loader = DataLoader(cifar10_train, batch_size=64, shuffle=True)
test_loader = DataLoader(cifar10_test, batch_size=64)

# Initialize the model and optimizer
model = SimpleNet(input_size=32*32*3, num_classes=10)
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)
criterion = nn.CrossEntropyLoss()

# Training loop
num_epochs = 10
```

```
for epoch in range(num_epochs):
    model.train()
    for inputs, labels in train_loader:
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

# Evaluate the model on the test set
model.eval()
correct = 0
total = 0
with torch.no_grad():
    for inputs, labels in test_loader:
        outputs = model(inputs)
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

accuracy = 100 * correct / total
print(f"3-Layer Neural Network Accuracy: {accuracy:.2f}%")
```

Output:

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ./data/cifar-10-python.tar.gz
100%|██████████| 170498071/170498071 [00:03<00:00, 42993818.54it/s]
Extracting ./data/cifar-10-python.tar.gz to ./data
Files already downloaded and verified
3-Layer Neural Network Accuracy: 53.74%
```

Applications

- Text mining
- Agriculture
- Finance
- Medical
- Facial recognition

Program 3

Implement Object detection using Faster RCNN Network.

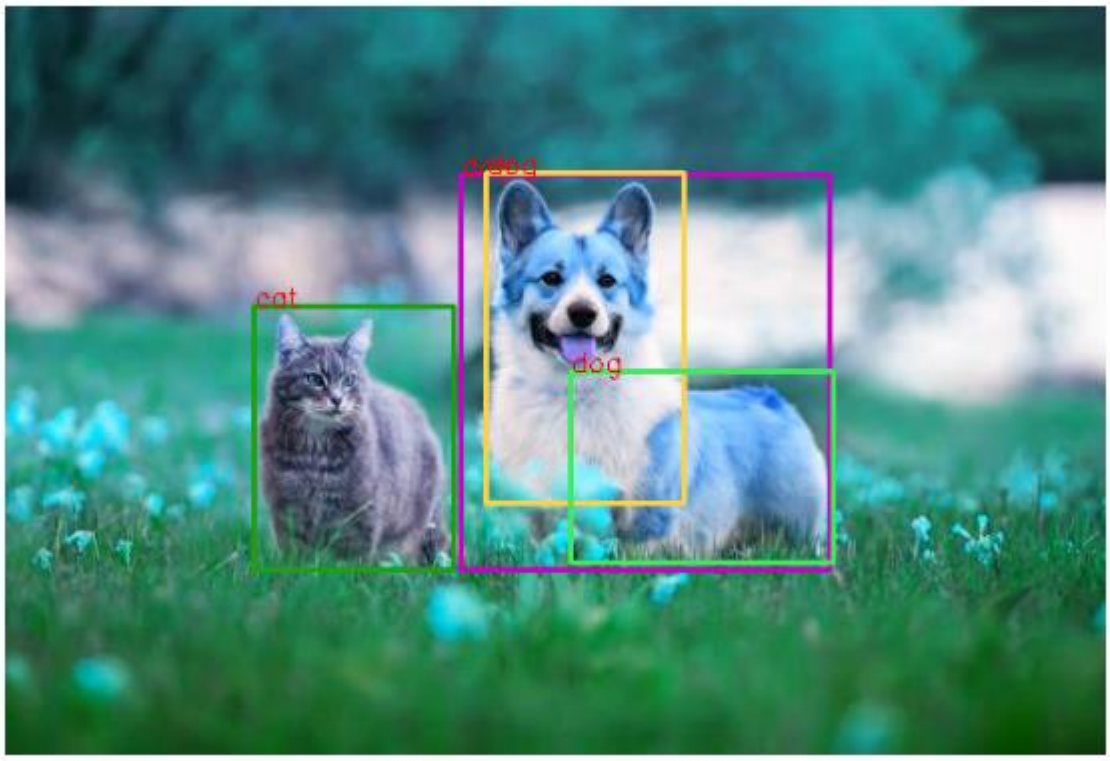
Program

```
from PIL import Image
import cv2
import matplotlib.pyplot as plt
import numpy as np
import torch
import torchvision.transforms as T
import torchvision

from google.colab import drive
drive.mount('/content/drive')

# Download the pre-trained model from Pytorch repository

model = torchvision.models.detection.fasterrcnn_resnet50_fpn(pretrained=True)
print("type(model): \t", type(model), "\n")
print("model: \n", model, "\n")

# Set the model to evaluation mode; this step is IMPORTANT
model.eval()
# Getting the list of all categories used to train the Faster R-CNN network
# Predictions from this list are supposed to be returned

COCO_INSTANCE_CATEGORY_NAMES = [
    '__background__', 'person', 'bicycle', 'car', 'motorcycle', 'airplane', 'bus',
    'train', 'truck', 'boat', 'traffic light', 'fire hydrant', 'N/A', 'stop sign',
    'parking meter', 'bench', 'bird', 'cat', 'dog', 'horse', 'sheep', 'cow',
    'elephant', 'bear', 'zebra', 'giraffe', 'N/A', 'backpack', 'umbrella', 'N/A', 'N/A',
    'handbag', 'tie', 'suitcase', 'frisbee', 'skis', 'snowboard', 'sports ball',
    'kite', 'baseball bat', 'baseball glove', 'skateboard', 'surfboard', 'tennis racket',
    'bottle', 'N/A', 'wine glass', 'cup', 'fork', 'knife', 'spoon', 'bowl',
    'banana', 'apple', 'sandwich', 'orange', 'broccoli', 'carrot', 'hot dog', 'pizza',
    'donut', 'cake', 'chair', 'couch', 'potted plant', 'bed', 'N/A', 'dining table',
    'N/A', 'N/A', 'toilet', 'N/A', 'tv', 'laptop', 'mouse', 'remote', 'keyboard', 'cell phone',
    'microwave', 'oven', 'toaster', 'sink', 'refrigerator', 'N/A', 'book',
    'clock', 'vase', 'scissors', 'teddy bear', 'hair drier', 'toothbrush'
]

print("Faster R-CNN network train on ", len(COCO_INSTANCE_CATEGORY_NAMES), " object categories")
THRESHOLD = 0.8
test_image_path ='/content/drive/MyDrive/VAP_GENAI_upendra/Object Detection
Datasets/dog_cat/val/images/cat_dog.jpg'
test_image = Image.open(test_image_path)
print("type(test_image): \t", test_image, "\n")

# transforming the test image to a Pytorch tensor
```

```
transform = T.Compose([T.ToTensor()])
test_image_tensor = transform(test_image)
print("type(test_image_tensor): \t", type(test_image_tensor), "\n")
print("test_image_tensor.size(): \t", test_image_tensor.size(), "\n")
print("test_image_tensor: \n", test_image_tensor, "\n")

# Make predictions on the test image using pre-trained model

predictions = model([test_image_tensor])
print("type(predictions): \t", type(predictions), "\n")
print("len(predictions): \t", len(predictions), "\n")
print("predictions: \n", predictions, "\n")

# Getting the actual predictions

prediction = predictions[0]
print("type(prediction): \t", type(prediction), "\n")

for key in prediction.keys():
    print(key, "\t", prediction[key])

# Extract the individual prediction components

bounding_boxes = prediction['boxes']
print("bounding_boxes: \n", bounding_boxes, "\n")

# Detach the bounding boxes from the computation graph

bounding_boxes = bounding_boxes.detach()
print("bounding_boxes: \n", bounding_boxes, "\n")

print("Number of bounding boxes (objects) detected: \t", bounding_boxes.size()[0], "\n")

# Extract the individual prediction components

class_labels = prediction['labels']

print("class_labels: \t\t\t\t", class_labels, "\n")
print("Number of bounding boxes (objects) detected: \t", class_labels.size()[0], "\n")

# Now  visualizing the detection results

# Swapping the axes to convret the dimension in the format (H, W, Channels)

test_image = cv2.imread(test_image_path)
test_image = cv2.cvtColor(test_image, cv2.COLOR_BGR2RGB)

print("Unannotated test image")
plt.imshow(test_image)
plt.show()

from google.colab.patches import cv2_imshow
```

```
font = cv2.FONT_HERSHEY_SIMPLEX
font_scale = 0.5
font_color = (0, 0, 255)  # White text color
font_thickness = 1


for box_index in range(bounding_boxes.size()[0]):
    print("Showing box: ", box_index+1, "\n")
    x1, y1, x2, y2 = bounding_boxes[box_index]
    random_color = list(np.random.choice(range(256), size=3))
    x1 = int(x1)
    x2 = int(x2)
    y1 = int(y1)
    y2 = int(y2)
    cv2.rectangle(test_image, (x1, y1), (x2, y2), (int(random_color[0]), int(random_color[1]),
int(random_color[2])), 2)
    cv2.putText(test_image, str(COCO_INSTANCE_CATEGORY_NAMES[int(class_labels[box_index])]), (x1,
y1), font, font_scale, font_color, font_thickness)
    cv2_imshow(test_image)
    print("\n\n")
```

Output:



Applications:

Object detection

Region Proposal Network (RPN)

Program 4

Train a CNN using Tensorflow and Keras

Program

```
import tensorflow as tf
from tensorflow import keras

# Load the CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()

# Preprocess the data
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0

# Define a simple CNN model
model = keras.Sequential([
    keras.layers.Conv2D(32, (3, 3), activation="relu", input_shape=(32, 32, 3)),
    keras.layers.MaxPooling2D((2, 2)),
    keras.layers.Flatten(),
    keras.layers.Dense(128, activation="relu"),
    keras.layers.Dense(10, activation="softmax")
])

# Compile the model
model.compile(optimizer="adam",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])

# Train the model
model.fit(x_train, y_train, epochs=10, batch_size=64, validation_split=0.2)

# Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(x_test, y_test)
print(f"Test accuracy: {test_accuracy * 100:.2f}%")
```

Output:

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 3s 0us/step
Epoch 1/10
625/625 [==============================] - 42s 63ms/step - loss: 1.5269 - accuracy: 0.4552 - val_loss: 1.3100 - val_accuracy: 0.5384
Epoch 2/10
625/625 [==============================] - 36s 58ms/step - loss: 1.2210 - accuracy: 0.5699 - val_loss: 1.2296 - val_accuracy: 0.5697
Epoch 3/10
625/625 [==============================] - 37s 59ms/step - loss: 1.1088 - accuracy: 0.6115 - val_loss: 1.1191 - val_accuracy: 0.6138
Epoch 4/10
625/625 [==============================] - 35s 57ms/step - loss: 1.0218 - accuracy: 0.6432 - val_loss: 1.1003 - val_accuracy: 0.6196
Epoch 5/10
625/625 [==============================] - 36s 57ms/step - loss: 0.9418 - accuracy: 0.6746 - val_loss: 1.0600 - val_accuracy: 0.6335
Epoch 6/10
625/625 [==============================] - 39s 62ms/step - loss: 0.8775 - accuracy: 0.6961 - val_loss: 1.0440 - val_accuracy: 0.6437
Epoch 7/10
625/625 [==============================] - 39s 62ms/step - loss: 0.8259 - accuracy: 0.7135 - val_loss: 1.0736 - val_accuracy: 0.6319
Epoch 8/10
625/625 [==============================] - 39s 62ms/step - loss: 0.7702 - accuracy: 0.7320 - val_loss: 1.0551 - val_accuracy: 0.6459
Epoch 9/10
625/625 [==============================] - 36s 58ms/step - loss: 0.7217 - accuracy: 0.7499 - val_loss: 1.0430 - val_accuracy: 0.6486
Epoch 10/10
625/625 [==============================] - 35s 56ms/step - loss: 0.6729 - accuracy: 0.7691 - val_loss: 1.0607 - val_accuracy: 0.6454
313/313 [==============================] - 4s 12ms/step - loss: 1.0715 - accuracy: 0.6375
Test accuracy: 63.75%
```

Applications:

Image Classification
Object Recognition
facial recognition, medical image analysis, self-driving cars

Program 5:

Improve the Deep learning model by tuning hyperparameters.

Program

```
import tensorflow as tf
from tensorflow import keras

# Load the CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()

# Preprocess the data
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0

# Data Augmentation
datagen = keras.preprocessing.image.ImageDataGenerator(
    rotation_range=15,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=True
)
datagen.fit(x_train)

# Define a deeper CNN model
model = keras.Sequential([
    keras.layers.Conv2D(32, (3, 3), activation="relu", input_shape=(32, 32, 3)),
    keras.layers.BatchNormalization(),
    keras.layers.Conv2D(64, (3, 3), activation="relu"),
    keras.layers.MaxPooling2D((2, 2)),
    keras.layers.BatchNormalization(),
    keras.layers.Conv2D(128, (3, 3), activation="relu"),
    keras.layers.GlobalAveragePooling2D(),
    keras.layers.Dense(128, activation="relu"),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(10, activation="softmax")
])

# Compile the model
model.compile(optimizer=keras.optimizers.Adam(lr=0.001),
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])

# Train the model with data augmentation
model.fit(datagen.flow(x_train, y_train, batch_size=64), epochs=20, validation_data=(x_test,
y_test))

# Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(x_test, y_test)
print(f"Test accuracy: {test_accuracy * 100:.2f}%")
```

Output

```
Epoch 12/20
782/782 [==============================] - 30s 39ms/step - loss: 0.8465 - accuracy: 0.1000 - val_loss: 0.9558 - val_accuracy: 0.1101
Epoch 13/20
782/782 [==============================] - 29s 38ms/step - loss: 0.8291 - accuracy: 0.1001 - val_loss: 0.8560 - val_accuracy: 0.0989
Epoch 14/20
782/782 [==============================] - 29s 37ms/step - loss: 0.8048 - accuracy: 0.1008 - val_loss: 0.8534 - val_accuracy: 0.1231
Epoch 15/20
782/782 [==============================] - 30s 38ms/step - loss: 0.7884 - accuracy: 0.1002 - val_loss: 0.8889 - val_accuracy: 0.0705
Epoch 16/20
782/782 [==============================] - 29s 38ms/step - loss: 0.7736 - accuracy: 0.1004 - val_loss: 0.8086 - val_accuracy: 0.1083
Epoch 17/20
782/782 [==============================] - 30s 38ms/step - loss: 0.7621 - accuracy: 0.1012 - val_loss: 0.7450 - val_accuracy: 0.1027
Epoch 18/20
782/782 [==============================] - 29s 37ms/step - loss: 0.7445 - accuracy: 0.1008 - val_loss: 0.8912 - val_accuracy: 0.1573
Epoch 19/20
782/782 [==============================] - 29s 37ms/step - loss: 0.7377 - accuracy: 0.0999 - val_loss: 0.7452 - val_accuracy: 0.1124
Epoch 20/20
782/782 [==============================] - 30s 38ms/step - loss: 0.7220 - accuracy: 0.1017 - val_loss: 0.8895 - val_accuracy: 0.0903
313/313 [==============================] - 1s 3ms/step - loss: 0.8895 - accuracy: 0.0903
Test accuracy: 9.03%
```

Applications:

Increasing model efficiency, robustness

Program 6

Perform Sentiment Analysis using RNN.

Program

```
from keras.datasets import imdb
from keras import Sequential
from keras.layers import Embedding, Dense, Dropout
from keras.layers import Activation, SimpleRNN

vocabulary_size = 5000
(X_train, y_train), (X_test, y_test) = imdb.load_data(num_words = vocabulary_size)
print('Loaded dataset with {} training samples, {} test samples'.format(len(X_train), len(X_test)))
print('---review---')
print(X_train[6])
print('---label---')
print(y_train[6])
word2id = imdb.get_word_index()
id2word = {i: word for word, i in word2id.items()}
print('---review with words---')
print([id2word.get(i, ' ') for i in X_train[6]])
print('---label---')
print(y_train[6])
print('Maximum review length: {}'.format(
len(max((X_train + X_test), key=len))))
print('Minimum review length: {}'.format(
len(min((X_test + X_test), key=len))))
from keras.preprocessing import sequence
max_words = 500
X_train = sequence.pad_sequences(X_train, maxlen=max_words)
X_test = sequence.pad_sequences(X_test, maxlen=max_words)
embedding_size=32
model=Sequential()
model.add(Embedding(vocabulary_size, embedding_size, input_length=max_words))
model.add(SimpleRNN(100))
model.add(Dense(1, activation='sigmoid'))
```

```
print(model.summary())


model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
batch_size = 64
num_epochs = 1
X_valid, y_valid = X_train[:batch_size], y_train[:batch_size]
X_train2, y_train2 = X_train[batch_size:], y_train[batch_size:]
model.fit(X_train2, y_train2, validation_data=(X_valid, y_valid), batch_size=batch_size, epochs=num_epochs)
scores = model.evaluate(X_test, y_test, verbose=0)
print('Test accuracy:', scores[1])
```

Output: `Test accuracy: 0.6672000288963318`

Application:

Speech recognition, voice recognition, time series prediction, and natural language processing

Program 7

Design a Chatbot using bi-directional LSTMs

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Sample training data
training_data = [
    "Hello",
    "Hi",
    "How are you?",
    "I'm doing well, thanks!",
    "What's your name?",
    "I'm a chatbot.",
    "Tell me a joke",
    "Why don't scientists trust atoms?",
    "Because they make up everything!",
    "exit"
]

# Tokenize the training data
tokenizer = Tokenizer()
tokenizer.fit_on_texts(training_data)
total_words = len(tokenizer.word_index) + 1

# Create input sequences and labels
input_sequences = []
for line in training_data:
    token_list = tokenizer.texts_to_sequences([line])[0]
    for i in range(1, len(token_list)):
        n_gram_sequence = token_list[:i+1]
        input_sequences.append(n_gram_sequence)

# Pad sequences
max_sequence_length = max([len(seq) for seq in input_sequences])
input_sequences = pad_sequences(input_sequences, maxlen=max_sequence_length,
padding='pre')

# Create inputs and labels
input_sequences = np.array(input_sequences)
X, y = input_sequences[:, :-1], input_sequences[:, -1]
y = tf.keras.utils.to_categorical(y, num_classes=total_words)

# Build the model
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Embedding(total_words, 64, input_length=max_sequence_length - 1))
model.add(tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(20)))
model.add(tf.keras.layers.Dense(total_words, activation='softmax'))
```

```
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

# Train the model
model.fit(X, y, epochs=100, verbose=1)

# Function to generate a response
def generate_response(input_text):
    input_seq = tokenizer.texts_to_sequences([input_text])[0]
    input_seq = pad_sequences([input_seq], maxlen=max_sequence_length - 1, padding='pre')
    predicted_probs = model.predict(input_seq)[0]
    predicted_id = np.argmax(predicted_probs)

    # Check if predicted_id is within a valid range
    if predicted_id >= 1 and predicted_id <= len(tokenizer.word_index):
        predicted_word = list(tokenizer.word_index.keys())[predicted_id - 1]
    else:
        predicted_word = "UNKNOWN_WORD"

    return predicted_word

# Chat with the bot
user_input = "Hello"
while user_input != "exit":
    response = generate_response(user_input)
    print(f"User: {user_input}")
    print(f"Chatbot: {response}")
    user_input = input("You: ")
```

Output:

```
1/1 [==============================] - 0s 16ms/step - loss: 1.4513 - accuracy: 0.8500
Epoch 100/100
1/1 [==============================] - 0s 19ms/step - loss: 1.4191 - accuracy: 0.8500
1/1 [==============================] - 1s 877ms/step
User: Hello
Chatbot: a
You: how are you
1/1 [==============================] - 0s 22ms/step
User: how are you
Chatbot: you
You: im fine
1/1 [==============================] - 0s 21ms/step
User: im fine
Chatbot: a
You: what is a
1/1 [==============================] - 0s 26ms/step
User: what is a
Chatbot: chatbot
You: what's your name?
1/1 [==============================] - 0s 24ms/step
User: what's your name?
Chatbot: name
You: exit
```

Applications :

Sentiment analysis, language modeling, speech recognition, and video analysis.

ADDITIONAL PROGRAMS

1. Write a program to count the number of items in a list

```
count = 0
for itervar in [3, 41, 12, 9, 74, 15]:
    count = count + 1
print('Count: ', count)
```

2. Write a program to find the largest value in a list or sequence

```
largest = None
print('Before:', largest)
for itervar in [3, 41, 12, 9, 74, 15]:
    if largest is None or itervar > largest :
        largest = itervar
    print('Loop:', itervar, largest)
print('Largest:', largest)
```

3. Write a program to find the smallest value in a list or sequence

```
smallest = None
print('Before:', smallest)
for itervar in [3, 41, 12, 9, 74, 15]:
    if smallest is None or itervar < smallest:
        smallest = itervar
    print('Loop:', itervar, smallest)
print('Smallest:', smallest)
```

4. Write a program which repeatedly reads numbers until the user enters "done". Once "done" is entered, print out the total, count, and average of the numbers. If the user enters anything other than a number, detect their mistake using try and except and print an error message and skip to the next number.

```
total = 0
count = 0
while (True):
            inp = input('enter a number')
            if inp == 'done':
                    break
            try:
                    value = int(inp)
            except:
                    print ('invalid input')
                    continue
            count = count + 1
            total = total + value

average = total/count
print('total:', total)
print('count:', count)
print('average:',average)
```

5. Write a program to open the file romeo.txt and read it line by line. For each line, split the line into a list of words using the split function. For each word, check to see if the word is already in a list. If the word is not in the list, add it to the list. When the program completes, sort and print the resulting words in alphabetical order.

```
newlst = list()
fin = open('romeo.txt')
for line in fin:
    line = line.rstrip()
    words =  line.split()
    for word in words:
            if word not in newlst:
                    newlst.append(word)
print(newlst)
```

6. Write the program that prompts the user for a list of numbers and prints out the maximum and minimum of the numbers at the end when the user enters "done". Write the program to store the numbers the user enters in a list and use the max() and min() functions to compute the maximum and minimum numbers after the loop completes.

```
newlst = list()
while(True):
    val = input('Enter the number')
    if val == 'done':
             break;
    newlst.append(float(val))
print('Maximum of number:  ',max(newlst))
print('Minimum of number:  ',min(newlst))
```

7. Write a function named **move_rectangle** that takes a Rectangle and two numbers named **dx** and **dy**. It should change the location of the rectangle by adding **dx** to the **x** coordinate of corner and adding **dy** to the **y** coordinate of corner

```
def move_rectangle(rect,dx,dy):
    rect.corner.x += dx
    rect.corner.y += dy
```

VIVA QUESTIONS

1. What's the difference between bias and variance?

Bias is error due to erroneous or overly simplistic assumptions in the learning algorithm. This can lead to the model underfitting your data, making it hard for it to have high predictive accuracy

Variance is error due to too much complexity in the learning algorithm. This leads to the algorithm being highly sensitive to high degrees of variation in your training data, which can lead your model to overfit the data.

2. What is the difference between supervised and unsupervised machine learning?

Supervised learning requires training labeled data. For example, in order to do classification (a supervised learning task), you'll need to first label the data you'll use to train the model to classify data into your labeled groups. Unsupervised learning, in contrast, does not require labeling data explicitly.

3. How is KNN different from k-means clustering?

K-Nearest Neighbors is a supervised classification algorithm, while k-means clustering is an unsupervised clustering algorithm. While the mechanisms may seem similar at first, what this really means is that in order for K-Nearest Neighbors to work, you need labeled data you want to classify an unlabeled point into (thus the nearest neighbor part). K-means clustering requires only a set of unlabeled points and a threshold: the algorithm will take unlabeled points and gradually learn how to cluster them into groups by computing the mean of the distance between different points.

The critical difference here is that KNN needs labeled points and is thus supervised learning, while k-means doesn't — and is thus unsupervised learning.

4. Explain how a ROC curve works.

The ROC curve is a graphical representation of the contrast between true positive rates and the false positive rate at various thresholds. It's often used as a proxy for the trade-off between the sensitivity of the model (true positives) vs the fall-out or the probability it will trigger a false alarm (false positives).

5. Define precision and recall.

Recall is also known as the true positive rate: the amount of positives your model claims compared to the actual number of positives there are throughout the data. Precision is also known as the positive predictive value, and it is a measure of the amount of accurate positives your model claims compared to the number of positives it actually claims.

6. What is Bayes' Theorem? How is it useful in a machine learning context?

Bayes' Theorem gives you the posterior probability of an event given what is known as prior knowledge.

7. Why is "Naive" Bayes naive?

Despite its practical applications, especially in text mining, Naive Bayes is considered "Naive" because it makes an assumption that is virtually impossible to see in real-life data: the conditional probability is calculated as the pure product of the individual probabilities of components. This implies the absolute independence of features — a condition probably never met in real life.

8. Explain the difference between L1 and L2 regularization.

L2 regularization tends to spread error among all the terms, while L1 is more binary/sparse, with many variables either being assigned a 1 or 0 in weighting. L1 corresponds to setting a Laplacean prior on the terms, while L2 corresponds to a Gaussian prior.

9. What's your favorite algorithm, and can you explain it to me in less than a minute?

This type of question tests your understanding of how to communicate complex and technical nuances with poise and the ability to summarize quickly and efficiently. Make sure you have a choice and make sure you can explain different algorithms so simply and effectively that a five-year-old could grasp the basics.

10. What's the difference between a generative and discriminative model?

A generative model will learn categories of data while a discriminative model will simply learn the distinction between different categories of data. Discriminative models will generally outperform generative models on classification tasks.

11. What cross-validation technique would you use on a time series dataset?

Instead of using standard k-folds cross-validation, you have to pay attention to the fact that a time series is not randomly distributed data — it is inherently ordered by chronological order.

12. How is a decision tree pruned?

Pruning is what happens in decision trees when branches that have weak predictive power are removed in order to reduce the complexity of the model and increase the predictive accuracy of a decision tree model. Pruning can happen bottom-up and top-down, with approaches such as reduced error pruning and cost complexity pruning.

13. What's the F1 score? How would you use it?

The F1 score is a measure of a model's performance. It is a weighted average of the precision and recall of a model, with results tending to 1 being the best, and those tending to 0 being the worst. You would use it in classification tests where true negatives don't matter much.

14. How would you handle an imbalanced dataset?

An imbalanced dataset is when you have, for example, a classification test and 90% of the data is in one class. That leads to problems: an accuracy of 90% can be skewed if you have no predictive power on the other category of data! Here are a few tactics to get over the hump:

i) Collect more data to even the imbalances in the dataset.

ii) Resample the dataset to correct for imbalances
iii) Try a different algorithm altogether on your dataset.

15. When should you use classification over regression?

Classification produces discrete values and dataset to strict categories, while regression gives you continuous results that allow you to better distinguish differences between individual points.

16. How do you ensure you're not overfitting with a model?

This is a simple restatement of a fundamental problem in machine learning: the possibility of overfitting training data and carrying the noise of that data through to the test set, thereby providing inaccurate generalizations.

There are three main methods to avoid overfitting:

i) Keep the model simpler: reduce variance by taking into account fewer variables and parameters, thereby removing some of the noise in the training data.
ii) Use cross-validation techniques such as k-folds cross-validation.
iii) Use regularization techniques such as LASSO that penalize certain model parameters if they're likely to cause overfitting.