Automatic Speech Recognition using CTC

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Description: Training a CTC-based model for automatic speech recognition.

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Introduction

Speech recognition is an interdisciplinary subfield of computer science and computational linguistics that develops methodologies and technologies that enable the recognition and translation of spoken language into text by computers. It is also known as automatic speech recognition (ASR), computer speech recognition or speech to text (STT). It incorporates knowledge and research in the computer science, linguistics and computer engineering fields.

This demonstration shows how to combine a 2D CNN, RNN and a Connectionist Temporal Classification (CTC) loss to build an ASR. CTC is an algorithm used to train deep neural networks in speech recognition, handwriting recognition and other sequence problems. CTC is used when we don't know how the input aligns with the output (how the characters in the transcript align to the audio). The model we create is similar to DeepSpeech2.

We will use the LJSpeech dataset from the LibriVox project. It consists of short audio clips of a single speaker reading passages from 7 non-fiction books.

We will evaluate the quality of the model using Word Error Rate (WER). WER is obtained by adding up the substitutions, insertions, and deletions that occur in a sequence of recognized words. Divide that number by the total number of words originally spoken. The result is the WER. To get the WER score you need to install the jiwer package. You can use the following command line:

```
pip install jiwer
```

References:

- LJSpeech Dataset
- Speech recognition
- Sequence Modeling With CTC
- DeepSpeech2

Setup

```
import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import matplotlib.pyplot as plt
from IPython import display
from jiwer import wer
```

Load the LJSpeech Dataset

Let's download the LJSpeech Dataset. The dataset contains 13,100 audio files as `wav` files in the `/wavs/` folder. The label (transcript) for each audio file is a string given in the `metadata.csv` file. The fields are:

- **ID**: this is the name of the corresponding .wav file
- **Transcription**: words spoken by the reader (UTF-8)
- **Normalized transcription**: transcription with numbers, ordinals, and monetary units expanded into full words (UTF-8).

For this demo we will use on the "Normalized transcription" field.

Each audio file is a single-channel 16-bit PCM WAV with a sample rate of 22,050 Hz.

```
data_url = "https://data.keithito.com/data/speech/LJSpeech-1.1.tar.bz2"
data_path = keras.utils.get_file("LJSpeech-1.1", data_url, untar=True)
wavs_path = data_path + "/wavs/"
metadata_path = data_path + "/metadata.csv"


# Read metadata file and parse it
metadata_df = pd.read_csv(metadata_path, sep="|", header=None, quoting=3)
metadata_df.columns = ["file_name", "transcription", "normalized_transcription"]
metadata_df = metadata_df[["file_name", "normalized_transcription"]]
metadata_df = metadata_df.sample(frac=1).reset_index(drop=True)
metadata_df.head(3)
```

	file_name	normalized_transcription
0	LJ029-0199	On November eighteen the Dallas City Council a...
1	LJ028-0237	with orders to march into the town by the bed ...
2	LJ009-0116	On the following day the capital convicts, who...

We now split the data into training and validation set.

```
split = int(len(metadata_df) * 0.90)
df_train = metadata_df[:split]
df_val = metadata_df[split:]

print(f"Size of the training set: {len(df_train)}")
print(f"Size of the training set: {len(df_val)}")
```

```
Size of the training set: 11790
Size of the training set: 1310
```

Preprocessing

We first prepare the vocabulary to be used.

```
# The set of characters accepted in the transcription.
characters = [x for x in "abcdefghijklmnopqrstuvwxyz'?! "]
# Mapping characters to integers
char_to_num = keras.layers.StringLookup(vocabulary=characters, oov_token="")
# Mapping integers back to original characters
num_to_char = keras.layers.StringLookup(
    vocabulary=char_to_num.get_vocabulary(), oov_token="", invert=True
)

print(
    f"The vocabulary is: {char_to_num.get_vocabulary()} "
    f"(size ={char_to_num.vocabulary_size()})"
)
```

```
The vocabulary is: ['', 'a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l', 'm', 'n',
'o', 'p', 'q', 'r', 's', 't', 'u', 'v', 'w', 'x', 'y', 'z', "'", '?', '!', ' '] (size =31)
```

Next, we create the function that describes the transformation that we apply to each element of our dataset.

```
# An integer scalar Tensor. The window length in samples.
frame_length = 256
# An integer scalar Tensor. The number of samples to step.
frame_step = 160
# An integer scalar Tensor. The size of the FFT to apply.
# If not provided, uses the smallest power of 2 enclosing frame_length.
fft_length = 384


def encode_single_sample(wav_file, label):
    ###########################################
    ##  Process the Audio
    ##########################################
    # 1. Read wav file
    file = tf.io.read_file(wavs_path + wav_file + ".wav")
    # 2. Decode the wav file
    audio, _ = tf.audio.decode_wav(file)
    audio = tf.squeeze(audio, axis=-1)
    # 3. Change type to float
    audio = tf.cast(audio, tf.float32)
    # 4. Get the spectrogram
    spectrogram = tf.signal.stft(
        audio, frame_length=frame_length, frame_step=frame_step, fft_length=fft_length
    )
    # 5. We only need the magnitude, which can be derived by applying tf.abs
    spectrogram = tf.abs(spectrogram)
    spectrogram = tf.math.pow(spectrogram, 0.5)
    # 6. normalisation
    means = tf.math.reduce_mean(spectrogram, 1, keepdims=True)
    stddevs = tf.math.reduce_std(spectrogram, 1, keepdims=True)
    spectrogram = (spectrogram - means) / (stddevs + 1e-10)
    ###########################################
    ##  Process the label
    ##########################################
    # 7. Convert label to Lower case
    label = tf.strings.lower(label)
    # 8. Split the label
    label = tf.strings.unicode_split(label, input_encoding="UTF-8")
    # 9. Map the characters in label to numbers
    label = char_to_num(label)
    # 10. Return a dict as our model is expecting two inputs
    return spectrogram, label
```

Creating `Dataset` objects

We create a `tf.data.Dataset` object that yields the transformed elements, in the same order as they appeared in the input.

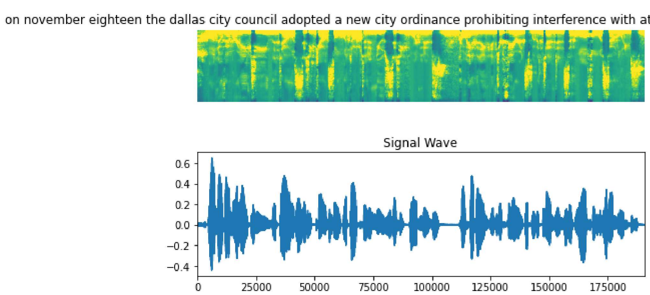
```
batch_size = 32
# Define the trainig dataset
train_dataset = tf.data.Dataset.from_tensor_slices(
    (list(df_train["file_name"]), list(df_train["normalized_transcription"]))
)
train_dataset = (
    train_dataset.map(encode_single_sample, num_parallel_calls=tf.data.AUTOTUNE)
    .padded_batch(batch_size)
    .prefetch(buffer_size=tf.data.AUTOTUNE)
)

# Define the validation dataset
validation_dataset = tf.data.Dataset.from_tensor_slices(
    (list(df_val["file_name"]), list(df_val["normalized_transcription"]))
)
validation_dataset = (
    validation_dataset.map(encode_single_sample, num_parallel_calls=tf.data.AUTOTUNE)
    .padded_batch(batch_size)
    .prefetch(buffer_size=tf.data.AUTOTUNE)
)
```

Visualize the data

Let's visualize an example in our dataset, including the audio clip, the spectrogram and the corresponding label.

```
fig = plt.figure(figsize=(8, 5))
for batch in train_dataset.take(1):
    spectrogram = batch[0][0].numpy()
    spectrogram = np.array([np.trim_zeros(x) for x in np.transpose(spectrogram)])
    label = batch[1][0]
    # Spectrogram
    label = tf.strings.reduce_join(num_to_char(label)).numpy().decode("utf-8")
    ax = plt.subplot(2, 1, 1)
    ax.imshow(spectrogram, vmax=1)
    ax.set_title(label)
    ax.axis("off")
    # Wav
    file = tf.io.read_file(wavs_path + list(df_train["file_name"])[0] + ".wav")
    audio, _ = tf.audio.decode_wav(file)
    audio = audio.numpy()
    ax = plt.subplot(2, 1, 2)
    plt.plot(audio)
    ax.set_title("Signal Wave")
    ax.set_xlim(0, len(audio))
    display.display(display.Audio(np.transpose(audio), rate=16000))
plt.show()
```

0:00 / 0:11



Model

We first define the CTC Loss function.

```
def CTCLoss(y_true, y_pred):
    # Compute the training-time loss value
    batch_len = tf.cast(tf.shape(y_true)[0], dtype="int64")
    input_length = tf.cast(tf.shape(y_pred)[1], dtype="int64")
    label_length = tf.cast(tf.shape(y_true)[1], dtype="int64")

    input_length = input_length * tf.ones(shape=(batch_len, 1), dtype="int64")
    label_length = label_length * tf.ones(shape=(batch_len, 1), dtype="int64")

    loss = keras.backend.ctc_batch_cost(y_true, y_pred, input_length, label_length)
    return loss
```

We now define our model. We will define a model similar to [DeepSpeech2](https://arxiv.org/abs/1512.02595).

```python
def build_model(input_dim, output_dim, rnn_layers=5, rnn_units=128):
    """Model similar to DeepSpeech2."""
    # Model's input
    input_spectrogram = layers.Input((None, input_dim), name="input")
    # Expand the dimension to use 2D CNN.
    x = layers.Reshape((-1, input_dim, 1), name="expand_dim")(input_spectrogram)
    # Convolution layer 1
    x = layers.Conv2D(
        filters=32,
        kernel_size=[11, 41],
        strides=[2, 2],
        padding="same",
        use_bias=False,
        name="conv_1",
    )(x)
    x = layers.BatchNormalization(name="conv_1_bn")(x)
    x = layers.ReLU(name="conv_1_relu")(x)
    # Convolution layer 2
    x = layers.Conv2D(
        filters=32,
        kernel_size=[11, 21],
        strides=[1, 2],
        padding="same",
        use_bias=False,
        name="conv_2",
    )(x)
    x = layers.BatchNormalization(name="conv_2_bn")(x)
    x = layers.ReLU(name="conv_2_relu")(x)
    # Reshape the resulted volume to feed the RNNs layers
    x = layers.Reshape((-1, x.shape[-2] * x.shape[-1]))(x)
    # RNN layers
    for i in range(1, rnn_layers + 1):
        recurrent = layers.GRU(
            units=rnn_units,
            activation="tanh",
            recurrent_activation="sigmoid",
            use_bias=True,
            return_sequences=True,
            reset_after=True,
            name=f"gru_{i}",
        )
        x = layers.Bidirectional(
            recurrent, name=f"bidirectional_{i}", merge_mode="concat"
        )(x)
        if i < rnn_layers:
            x = layers.Dropout(rate=0.5)(x)
    # Dense layer
    x = layers.Dense(units=rnn_units * 2, name="dense_1")(x)
    x = layers.ReLU(name="dense_1_relu")(x)
    x = layers.Dropout(rate=0.5)(x)
    # Classification layer
    output = layers.Dense(units=output_dim + 1, activation="softmax")(x)
    # Model
    model = keras.Model(input_spectrogram, output, name="DeepSpeech_2")
    # Optimizer
    opt = keras.optimizers.Adam(learning_rate=1e-4)
    # Compile the model and return
    model.compile(optimizer=opt, loss=CTCLoss)
    return model


# Get the model
model = build_model(
    input_dim=fft_length // 2 + 1,
    output_dim=char_to_num.vocabulary_size(),
    rnn_units=512,
)
model.summary(line_length=110)
```

```
Model: "DeepSpeech_2"

 Layer (type)                                Output Shape
Param #
==============================================================================================
 input (InputLayer)                          [(None, None, 193)]                     0

 expand_dim (Reshape)                        (None, None, 193, 1)                    0

 conv_1 (Conv2D)                             (None, None, 97, 32)
14432

 conv_1_bn (BatchNormalization)              (None, None, 97, 32)                    128

 conv_1_relu (ReLU)                          (None, None, 97, 32)                    0

 conv_2 (Conv2D)                             (None, None, 49, 32)
236544

 conv_2_bn (BatchNormalization)              (None, None, 49, 32)                    128

 conv_2_relu (ReLU)                          (None, None, 49, 32)                    0

 reshape (Reshape)                           (None, None, 1568)                      0

 bidirectional_1 (Bidirectional)             (None, None, 1024)
6395904

 dropout (Dropout)                           (None, None, 1024)                      0

 bidirectional_2 (Bidirectional)             (None, None, 1024)
4724736

 dropout_1 (Dropout)                         (None, None, 1024)                      0

 bidirectional_3 (Bidirectional)             (None, None, 1024)
4724736

 dropout_2 (Dropout)                         (None, None, 1024)                      0

 bidirectional_4 (Bidirectional)             (None, None, 1024)
4724736

 dropout_3 (Dropout)                         (None, None, 1024)                      0

 bidirectional_5 (Bidirectional)             (None, None, 1024)
4724736

 dense_1 (Dense)                             (None, None, 1024)
1049600

 dense_1_relu (ReLU)                         (None, None, 1024)                      0

 dropout_4 (Dropout)                         (None, None, 1024)                      0

 dense (Dense)                               (None, None, 32)
32800

==============================================================================================
Total params: 26,628,480
Trainable params: 26,628,352
Non-trainable params: 128
```

Training and Evaluating

```
# A utility function to decode the output of the network
def decode_batch_predictions(pred):
    input_len = np.ones(pred.shape[0]) * pred.shape[1]
    # Use greedy search. For complex tasks, you can use beam search
    results = keras.backend.ctc_decode(pred, input_length=input_len, greedy=True)[0][0]
    # Iterate over the results and get back the text
    output_text = []
    for result in results:
        result = tf.strings.reduce_join(num_to_char(result)).numpy().decode("utf-8")
        output_text.append(result)
    return output_text


# A callback class to output a few transcriptions during training
class CallbackEval(keras.callbacks.Callback):
    """Displays a batch of outputs after every epoch."""

    def __init__(self, dataset):
        super().__init__()
        self.dataset = dataset

    def on_epoch_end(self, epoch: int, logs=None):
        predictions = []
        targets = []
        for batch in self.dataset:
            X, y = batch
            batch_predictions = model.predict(X)
            batch_predictions = decode_batch_predictions(batch_predictions)
            predictions.extend(batch_predictions)
            for label in y:
                label = (
                    tf.strings.reduce_join(num_to_char(label)).numpy().decode("utf-8")
                )
                targets.append(label)
        wer_score = wer(targets, predictions)
        print("-" * 100)
        print(f"Word Error Rate: {wer_score:.4f}")
        print("-" * 100)
        for i in np.random.randint(0, len(predictions), 2):
            print(f"Target    : {targets[i]}")
            print(f"Prediction: {predictions[i]}")
            print("-" * 100)
```

Let's start the training process.

```
# Define the number of epochs.
epochs = 1
# Callback function to check transcription on the val set.
validation_callback = CallbackEval(validation_dataset)
# Train the model
history = model.fit(
    train_dataset,
    validation_data=validation_dataset,
    epochs=epochs,
    callbacks=[validation_callback],
)
```

```
369/369 [==============================] - ETA: 0s - loss: 302.4755----------------------------
----------------------------------------------------------------------
Word Error Rate: 1.0000
------------------------------------------------------------------------------------------------
----
Target    : special agent lyndal l shaneyfelt a photography expert with the fbi
Prediction: s
------------------------------------------------------------------------------------------------
----
Target    : dissolved in water the sugar is transported down delicate tubes chiefly in the
growing bark region of the stem
Prediction: sss
------------------------------------------------------------------------------------------------
----
369/369 [==============================] - 407s 1s/step - loss: 302.4755 - val_loss: 252.1534
```

Inference

```python
# Let's check results on more validation samples
predictions = []
targets = []
for batch in validation_dataset:
    X, y = batch
    batch_predictions = model.predict(X)
    batch_predictions = decode_batch_predictions(batch_predictions)
    predictions.extend(batch_predictions)
    for label in y:
        label = tf.strings.reduce_join(num_to_char(label)).numpy().decode("utf-8")
        targets.append(label)
wer_score = wer(targets, predictions)
print("-" * 100)
print(f"Word Error Rate: {wer_score:.4f}")
print("-" * 100)
for i in np.random.randint(0, len(predictions), 5):
    print(f"Target    : {targets[i]}")
    print(f"Prediction: {predictions[i]}")
    print("-" * 100)
```

```
------------------------------------------------------------------------------------------------
----
Word Error Rate: 1.0000
------------------------------------------------------------------------------------------------
----
Target    : the owners of the latter would then issue a second set of warrants on these goods in
total ignorance of the fact that they were already pledged
Prediction: ssnssss
------------------------------------------------------------------------------------------------
----
Target    : till the whole body of the slaves were manumitted in eighteen thirtythree
Prediction: sr
------------------------------------------------------------------------------------------------
----
Target    : the committee most of all insisted upon the entire individual separation of
prisoners except during the hours of labor
Prediction: ssssss
------------------------------------------------------------------------------------------------
----
Target    : he made no attempt to help her and there are other indications that he did not want
her to learn that language
Prediction: s
------------------------------------------------------------------------------------------------
----
Target    : the building of the babylon so famous in history began with nabopolassar
Prediction: sssrs
------------------------------------------------------------------------------------------------
----
```

Conclusion

In practice, you should train for around 50 epochs or more. Each epoch takes approximately 5-6mn using a `GeForce RTX 2080 Ti` GPU. The model we trained at 50 epochs has a `Word Error Rate (WER) ≈ 16% to 17%`.

Some of the transcriptions around epoch 50:

Audio file: LJ017-0009.wav

```
- Target    : sir thomas overbury was undoubtedly poisoned by lord rochester in the reign
of james the first
- Prediction: cer thomas overbery was undoubtedly poisoned by lordrochester in the reign
of james the first
```

Audio file: LJ003-0340.wav

```
- Target    : the committee does not seem to have yet understood that newgate could be
only and properly replaced
- Prediction: the committee does not seem to have yet understood that newgate could be
only and proberly replace
```

Audio file: LJ011-0136.wav

```
- Target    : still no sentence of death was carried out for the offense and in eighteen
thirtytwo
- Prediction: still no sentence of death was carried out for the offense and in eighteen
thirtytwo
```

Example available on HuggingFace. | Trained Model | Demo | | :--: | :--: | | Model CTC ASR | Spaces CTC ASR |
