ex2_transfer_learning_stud

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1 Ex 2 - Transfer learning

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Student 2:

Student 3:

```
[ ]: import os
     import numpy as np

     import tensorflow as tf
     from tensorflow import keras
     import matplotlib.pyplot as plt
     import tensorflow_datasets as tfds

     from sklearn.metrics import accuracy_score
```

1.1 Load the Dataset and visualize it

```
[ ]: # Download and split the food101 dataset
     (train_ds, validation_ds, test_ds), info = tfds.load(
         "food101",
         split=["train", "validation[:50%]", "validation[50%:]"],
         as_supervised=True,
         with_info=True
     )
```

```
Downloading and preparing dataset 4.65 GiB (download: 4.65 GiB, generated:
Unknown size, total: 4.65 GiB) to /root/tensorflow_datasets/food101/2.0.0…

Dl Completed…: 0 url [00:00, ? url/s]

Dl Size…: 0 MiB [00:00, ? MiB/s]

Extraction completed…: 0 file [00:00, ? file/s]

Generating splits…:   0%|          | 0/2 [00:00<?, ? splits/s]

Generating train examples…:   0%|          | 0/75750 [00:00<?, ? examples/s]

Shuffling /root/tensorflow_datasets/food101/2.0.0.incompleteNCZJKJ/food101-train.
↪tfrecord*…:   0%|          …
```

```
Generating validation examples…:   0%|          | 0/25250 [00:00<?, ? examples/s]
```

```
Shuffling /root/tensorflow_datasets/food101/2.0.0.incompleteNCZJKJ/
↪food101-validation.tfrecord*…:   0%|      …
```

```
Dataset food101 downloaded and prepared to
/root/tensorflow_datasets/food101/2.0.0. Subsequent calls will reuse this data.
```

[ ]:
```python
# Filter the dataset to keep the first 20 classes only.
N_CLASSES = 20
CLASS_NAMES = info.features['label'].names[:N_CLASSES]

train_ds = train_ds.filter(lambda img, label: label < N_CLASSES)
validation_ds = validation_ds.filter(lambda img, label: label < N_CLASSES)
test_ds = test_ds.filter(lambda img, label: label < N_CLASSES)
```

[ ]:
```python
plt.figure(figsize=(10, 6))
for i, (image, label) in enumerate(train_ds.take(6)):
    ax = plt.subplot(2, 3, i + 1)
    plt.imshow(image)
    plt.title(CLASS_NAMES[label])
    plt.axis("off")
```

1.2 Resize and normalize

[ ]:
```
# Resize the images in the training, validation and test set
IMG_SIZE = 224
train_ds = train_ds.map(lambda img, label: (tf.image.resize(img, (IMG_SIZE,␣
↪IMG_SIZE)), label))
validation_ds = validation_ds.map(lambda img, label: (tf.image.resize(img,␣
↪(IMG_SIZE, IMG_SIZE)), label))
test_ds = test_ds.map(lambda img, label: (tf.image.resize(img, (IMG_SIZE,␣
↪IMG_SIZE)), label))
```

[ ]:
```
# Normalize the images
train_ds = train_ds.map(lambda img, label: (img / 255, label))
validation_ds = validation_ds.map(lambda img, label: (img / 255, label))
test_ds = test_ds.map(lambda img, label: (img / 255, label))
```

[ ]:
```
# One hot encode the labels
train_ds = train_ds.map(lambda img, label: (img, tf.one_hot(label, N_CLASSES)))
validation_ds = validation_ds.map(lambda img, label: (img, tf.one_hot(label,␣
↪N_CLASSES)))
test_ds = test_ds.map(lambda img, label: (img, tf.one_hot(label, N_CLASSES)))
```

[ ]:
```
BATCH_SIZE = 32
train_ds = train_ds.batch(BATCH_SIZE)
validation_ds = validation_ds.batch(BATCH_SIZE)
test_ds = test_ds.batch(BATCH_SIZE)
```

1.3 Data-Augmentation

[ ]:
```
# Optional define/implements data-augmentation
```

1.4 Training

1.4.1 Step 1: Only train the head of the network

[ ]:
```
%%time
# Load the pretrained model from the available models: https://keras.io/api/
↪applications/#available-models.
# Load the imagenet weights but do not include the ImageNet classifier at the␣
↪top.
#
# Tip, don't choose models that are too big because the training could take␣
↪hours.
# A model like mobilenet is more than enough for the exercise.

# Use MobileNetV22 as the base model
base_model = keras.applications.MobileNetV2(
    input_shape=(IMG_SIZE, IMG_SIZE, 3),
```

```
    include_top=False,
    weights='imagenet'
)

# Freeze the base_model
base_model.trainable = False

# Create the model structure
inputs = keras.Input(shape=(IMG_SIZE, IMG_SIZE, 3))
x = base_model(inputs, training=False)
x = keras.layers.GlobalAveragePooling2D()(x)
x = keras.layers.Dense(128, activation='relu')(x)
outputs = keras.layers.Dense(N_CLASSES, activation='softmax')(x)

model = keras.Model(inputs, outputs)

model.summary()
```

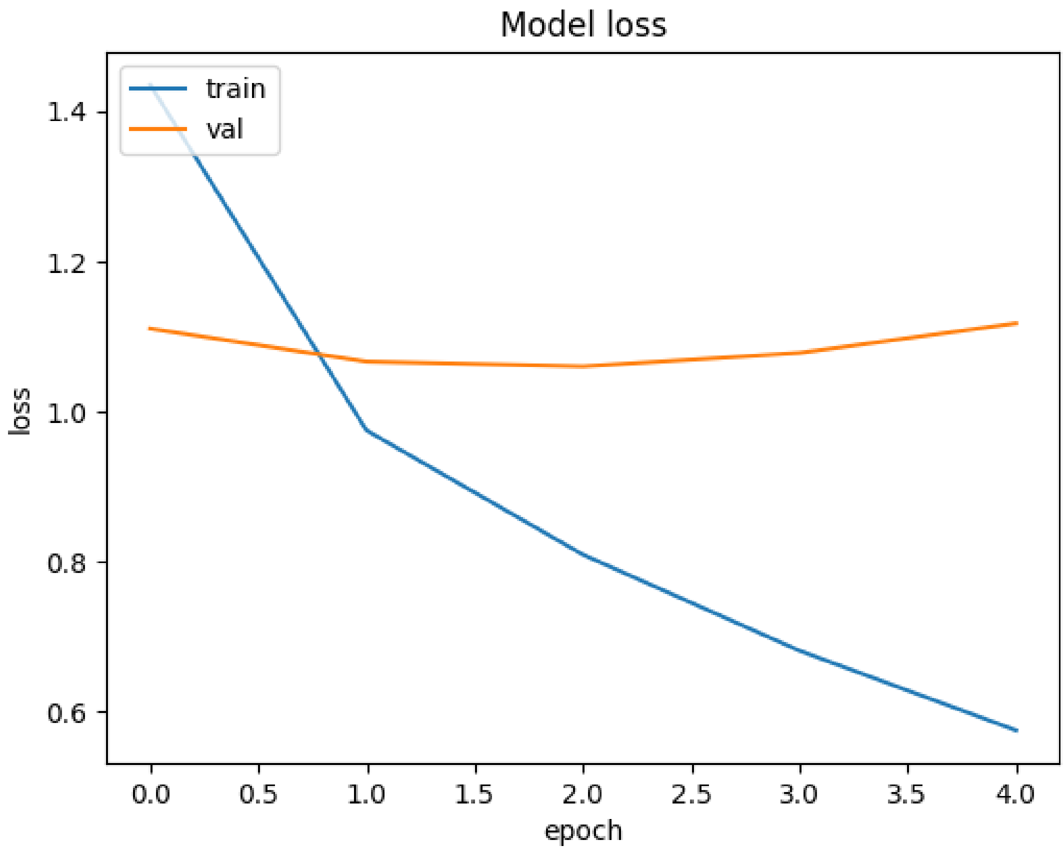
```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_4 (InputLayer)        [(None, 224, 224, 3)]     0

 mobilenetv2_1.00_224 (Func  (None, 7, 7, 1280)        2257984
 tional)

 global_average_pooling2d_1  (None, 1280)              0
  (GlobalAveragePooling2D)

 dense_2 (Dense)             (None, 128)               163968

 dense_3 (Dense)             (None, 20)                2580

=================================================================
Total params: 2424532 (9.25 MB)
Trainable params: 166548 (650.58 KB)
Non-trainable params: 2257984 (8.61 MB)
_________________________________________________________________
CPU times: user 1.85 s, sys: 17.4 ms, total: 1.87 s
Wall time: 1.98 s
```

[ ]:
```
%%time

# Compile the model with your optimizer, your loss and your metrics
model.compile(
    optimizer=keras.optimizers.Adam(1e-3),
```

```python
    loss=keras.losses.CategoricalCrossentropy(),
    metrics=[keras.metrics.CategoricalAccuracy()]
)

# Optional: Define and use callbacks
callbacks = [
    keras.callbacks.ModelCheckpoint("best_model.h5", save_best_only=True),
    keras.callbacks.EarlyStopping(patience=5, restore_best_weights=True)
]

step1_history = model.fit(train_ds, epochs=5, validation_data=validation_ds,␣
 ↪callbacks=callbacks)
```

```
Epoch 1/5
469/469 [==============================] - 112s 233ms/step - loss: 1.4352 -
categorical_accuracy: 0.5644 - val_loss: 1.1103 - val_categorical_accuracy:
0.6547
Epoch 2/5
469/469 [==============================] - 110s 235ms/step - loss: 0.9748 -
categorical_accuracy: 0.6997 - val_loss: 1.0664 - val_categorical_accuracy:
0.6647
Epoch 3/5
469/469 [==============================] - 103s 219ms/step - loss: 0.8093 -
categorical_accuracy: 0.7525 - val_loss: 1.0600 - val_categorical_accuracy:
0.6714
Epoch 4/5
469/469 [==============================] - 110s 235ms/step - loss: 0.6815 -
categorical_accuracy: 0.7944 - val_loss: 1.0780 - val_categorical_accuracy:
0.6762
Epoch 5/5
469/469 [==============================] - 105s 224ms/step - loss: 0.5756 -
categorical_accuracy: 0.8295 - val_loss: 1.1172 - val_categorical_accuracy:
0.6754
CPU times: user 14min 29s, sys: 32.1 s, total: 15min 1s
Wall time: 10min 48s
```

[ ]:
```python
def plot_history(history, metric):
    plt.plot(history.history[metric])
    plt.plot(history.history['val_'+metric])
    plt.title('Model '+metric)
    plt.ylabel(metric)
    plt.xlabel('epoch')
    plt.legend(['train', 'val'], loc='upper left')
    plt.show()

plot_history(step1_history, 'loss')
```



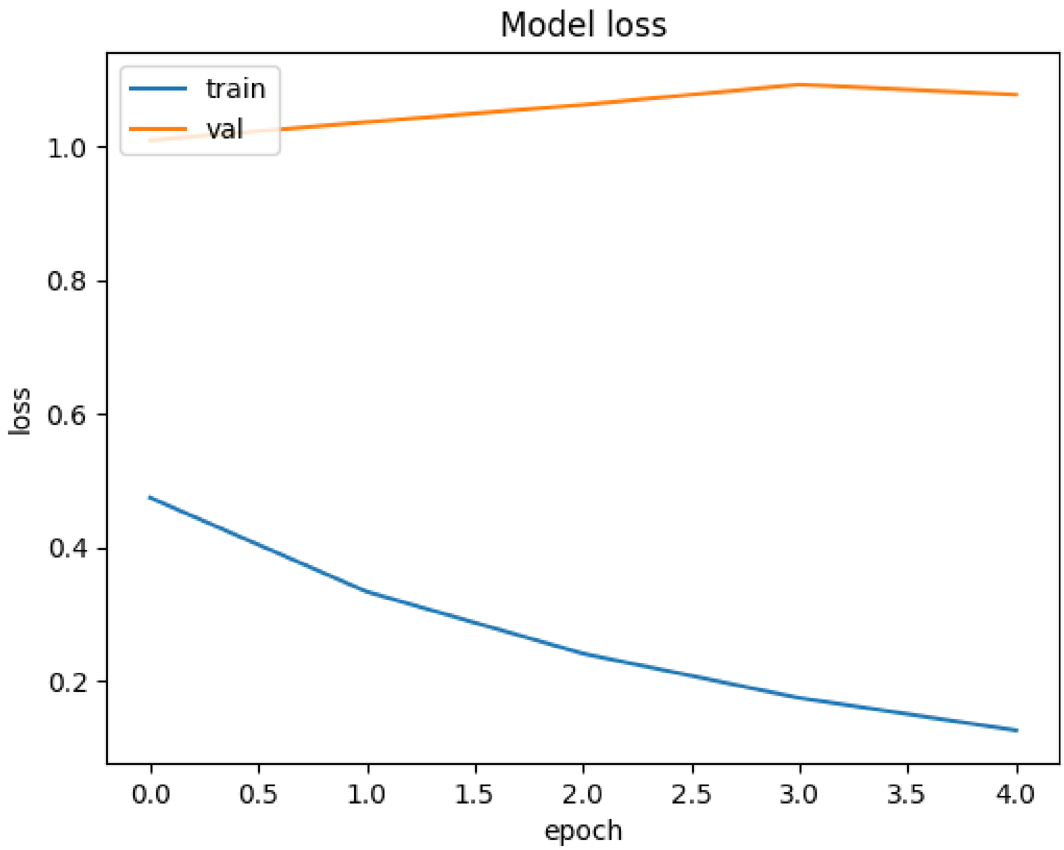
1.4.2 Step 2: Fine-Tune the whole model

[ ]:
```
%%time


# Unfreeze the pretrained base.

base_model.trainable = True


# Compile the model again
model.compile(
    optimizer=keras.optimizers.Adam(1e-5),
    loss=keras.losses.CategoricalCrossentropy(),
    metrics=[keras.metrics.CategoricalAccuracy()]
)


# Retrain the model
```

```
step2_history = model.fit(train_ds, epochs=5, validation_data=validation_ds,␣
↪callbacks=callbacks)
```

```
Epoch 1/5
469/469 [==============================] - 153s 269ms/step - loss: 0.4740 -
categorical_accuracy: 0.8540 - val_loss: 1.0096 - val_categorical_accuracy:
0.7092
Epoch 2/5
469/469 [==============================] - 123s 262ms/step - loss: 0.3331 -
categorical_accuracy: 0.9055 - val_loss: 1.0368 - val_categorical_accuracy:
0.7088
Epoch 3/5
469/469 [==============================] - 129s 275ms/step - loss: 0.2403 -
categorical_accuracy: 0.9414 - val_loss: 1.0627 - val_categorical_accuracy:
0.7116
Epoch 4/5
469/469 [==============================] - 129s 274ms/step - loss: 0.1738 -
categorical_accuracy: 0.9659 - val_loss: 1.0931 - val_categorical_accuracy:
0.7136
Epoch 5/5
469/469 [==============================] - 134s 285ms/step - loss: 0.1253 -
categorical_accuracy: 0.9811 - val_loss: 1.0779 - val_categorical_accuracy:
0.7204
CPU times: user 17min 32s, sys: 33.1 s, total: 18min 5s
Wall time: 11min 8s
```

```
[ ]: plot_history(step2_history, 'loss')
```



1.5 Test the fine-tuned model

[ ]:
```
%%time
# Predict the test set
y_pred = model.predict(test_ds, verbose=1)

# De-encode the onehot encoded labels
y_pred = np.argmax(y_pred, axis=1)
y_true = np.concatenate([np.argmax(y.numpy(), axis=1) for x, y in test_ds],␣
↪axis=0)
```

```
25/Unknown - 7s 219ms/step
```

[ ]:
```
%%time

# Accuracy
acc = accuracy_score(y_true, y_pred)
print("Accuracy:", acc)
```

[ ]:
```python
def show_images_prediction(page=0):
    test_examples = (np.concatenate([x.numpy() for x, y in test_ds])+1)/2*255
    test_examples = test_examples.astype("uint32")

    page_size = 20
    nrows = 4
    ncols = 5
    fig, axes = plt.subplots(nrows=nrows, ncols=ncols, figsize=(12, 12))
    fig.set_size_inches(20, 16)

    start_i = page * page_size
    for i, ax in enumerate(axes.flat):
        im = ax.imshow(test_examples[i+start_i])
        ax.set_axis_off()
        ax.set_title("Pred: "+CLASS_NAMES[y_pred[i+start_i]]+"\nTrue: "+CLASS_NAMES[y_true[i+start_i]])
        ax.xaxis.set_ticks([])
        ax.yaxis.set_ticks([])

    plt.show()
show_images_prediction(2)
```

[ ]:

```
```