10_transfer_learning

September 29, 2021

1 How to further train a pre-trained model

We will demonstrate how to freeze some or all of the layers of a pre-trained model and continue training using a new fully-connected set of layers and data with a different format.

Adapted from the Tensorflow 2.0 transfer learning tutorial.

1.1 Imports & Settings

[1]:
```
%matplotlib inline

from sklearn.datasets import load_files
import numpy as np
import pandas as pd
from pathlib import Path
import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter
import seaborn as sns

import tensorflow as tf
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.layers import Dense, Flatten, Dropout,␣
 ↪GlobalAveragePooling2D
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.callbacks import ModelCheckpoint, TensorBoard,␣
 ↪EarlyStopping

import tensorflow_datasets as tfds
```

[2]:
```
gpu_devices = tf.config.experimental.list_physical_devices('GPU')
if gpu_devices:
    print('Using GPU')
    tf.config.experimental.set_memory_growth(gpu_devices[0], True)
else:
    print('Using CPU')
```

```
Using CPU
```

[3]:
```
results_path = Path('results', 'transfer_learning')
if not results_path.exists():
    results_path.mkdir(parents=True)
```

[4]:
```
sns.set_style('whitegrid')
```

1.2 Load TensorFlow Cats vs Dog Dataset

TensorFlow includes a large number of built-in dataset:

[5]:
```
tfds.list_builders()
```

[5]:
```
['abstract_reasoning',
 'aflw2k3d',
 'amazon_us_reviews',
 'bair_robot_pushing_small',
 'bigearthnet',
 'binarized_mnist',
 'binary_alpha_digits',
 'caltech101',
 'caltech_birds2010',
 'caltech_birds2011',
 'cats_vs_dogs',
 'celeb_a',
 'celeb_a_hq',
 'chexpert',
 'cifar10',
 'cifar100',
 'cifar10_corrupted',
 'clevr',
 'cnn_dailymail',
 'coco',
 'coco2014',
 'coil100',
 'colorectal_histology',
 'colorectal_histology_large',
 'curated_breast_imaging_ddsm',
 'cycle_gan',
 'deep_weeds',
 'definite_pronoun_resolution',
 'diabetic_retinopathy_detection',
 'downsampled_imagenet',
 'dsprites',
 'dtd',
 'dummy_dataset_shared_generator',
```

```
'dummy_mnist',
'emnist',
'eurosat',
'fashion_mnist',
'flores',
'food101',
'gap',
'glue',
'groove',
'higgs',
'horses_or_humans',
'image_label_folder',
'imagenet2012',
'imagenet2012_corrupted',
'imdb_reviews',
'iris',
'kitti',
'kmnist',
'lfw',
'lm1b',
'lsun',
'mnist',
'mnist_corrupted',
'moving_mnist',
'multi_nli',
'nsynth',
'omniglot',
'open_images_v4',
'oxford_flowers102',
'oxford_iiit_pet',
'para_crawl',
'patch_camelyon',
'pet_finder',
'quickdraw_bitmap',
'resisc45',
'rock_paper_scissors',
'rock_you',
'scene_parse150',
'shapes3d',
'smallnorb',
'snli',
'so2sat',
'squad',
'stanford_dogs',
'stanford_online_products',
'starcraft_video',
'sun397',
```

```
 'super_glue',
 'svhn_cropped',
 'ted_hrlr_translate',
 'ted_multi_translate',
 'tf_flowers',
 'titanic',
 'trivia_qa',
 'uc_merced',
 'ucf101',
 'visual_domain_decathlon',
 'voc2007',
 'wikipedia',
 'wmt14_translate',
 'wmt15_translate',
 'wmt16_translate',
 'wmt17_translate',
 'wmt18_translate',
 'wmt19_translate',
 'wmt_t2t_translate',
 'wmt_translate',
 'xnli']
```

We will use a set of cats and dog images for binary classification.

[6]:
```
(raw_train, raw_validation, raw_test), metadata = tfds.load(
    'cats_vs_dogs',
    split=[
        tfds.Split.TRAIN.subsplit(tfds.percent[:80]),
        tfds.Split.TRAIN.subsplit(tfds.percent[80:90]),
        tfds.Split.TRAIN.subsplit(tfds.percent[90:])
    ],
    with_info=True,
    as_supervised=True,
    data_dir='../data/tensorflow'
)
```

[7]:
```
print('Raw train:\t', raw_train)
print('Raw validation:\t', raw_validation)
print('Raw test:\t', raw_test)
```

```
Raw train:        <_OptionsDataset shapes: ((None, None, 3), ()), types:
(tf.uint8, tf.int64)>
Raw validation:   <_OptionsDataset shapes: ((None, None, 3), ()), types:
(tf.uint8, tf.int64)>
Raw test:         <_OptionsDataset shapes: ((None, None, 3), ()), types:
(tf.uint8, tf.int64)>
```

1.2.1 Show sample images

[8]:
```
get_label_name = metadata.features['label'].int2str

for image, label in raw_train.take(2):
    plt.figure()
    plt.imshow(image)
    plt.title(get_label_name(label))
    plt.grid(False)
    plt.axis('off')
```

cat

1.3 Preprocessing

All images will be resized to 160x160:

[9]:
```
IMG_SIZE = 160
IMG_SHAPE = (IMG_SIZE, IMG_SIZE, 3)
```

[10]:
```
def format_example(image, label):
    image = tf.cast(image, tf.float32)
    image = (image/127.5) - 1
    image = tf.image.resize(image, (IMG_SIZE, IMG_SIZE))
    return image, label
```

[11]:
```
train = raw_train.map(format_example)
validation = raw_validation.map(format_example)
test = raw_test.map(format_example)
```

[12]:
```
BATCH_SIZE = 32
SHUFFLE_BUFFER_SIZE = 1000
```

[13]:
```
train_batches = train.shuffle(SHUFFLE_BUFFER_SIZE).batch(BATCH_SIZE)
validation_batches = validation.batch(BATCH_SIZE)
test_batches = test.batch(BATCH_SIZE)
```

[14]:
```
for image_batch, label_batch in train_batches.take(1):
    pass
```

```
image_batch.shape
```

[14]: TensorShape([32, 160, 160, 3])

1.4 Load the VGG-16 Bottleneck Features

We use the VGG16 weights, pre-trained on ImageNet with the much smaller 32 x 32 CIFAR10 data. Note that we indicate the new input size upon import and set all layers to not trainable:

[15]:
```
vgg16 = VGG16(input_shape=IMG_SHAPE, include_top=False, weights='imagenet')
vgg16.summary()
```

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 160, 160, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 160, 160, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 160, 160, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 80, 80, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 80, 80, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 80, 80, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 40, 40, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 40, 40, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 40, 40, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 40, 40, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 20, 20, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 20, 20, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 20, 20, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 20, 20, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 10, 10, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 10, 10, 512)       2359808
```

```
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 5, 5, 512)         0
=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

[16]:
```
feature_batch = vgg16(image_batch)
feature_batch.shape
```

[16]:
```
TensorShape([32, 5, 5, 512])
```

1.5 Freeze model layers

[17]:
```
vgg16.trainable = False
```

[18]:
```
vgg16.summary()
```

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 160, 160, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 160, 160, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 160, 160, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 80, 80, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 80, 80, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 80, 80, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 40, 40, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 40, 40, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 40, 40, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 40, 40, 256)       590080
_________________________________________________________________
```

```
block3_pool (MaxPooling2D)   (None, 20, 20, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 20, 20, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 20, 20, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 20, 20, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 10, 10, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 5, 5, 512)         0
=================================================================
Total params: 14,714,688
Trainable params: 0
Non-trainable params: 14,714,688
_________________________________________________________________
```

1.6 Add new layers to model

1.6.1 Using the Sequential model API

[19]:
```
global_average_layer = GlobalAveragePooling2D()
dense_layer = Dense(64, activation='relu')
dropout = Dropout(0.5)
prediction_layer = Dense(1, activation='sigmoid')
```

[20]:
```
seq_model = tf.keras.Sequential([vgg16,
                                 global_average_layer,
                                 dense_layer,
                                 dropout,
                                 prediction_layer])
```

[21]:
```
seq_model.compile(loss = tf.keras.losses.BinaryCrossentropy(from_logits=True),
                  optimizer = 'Adam',
                  metrics=["accuracy"])
```

[22]:
```
seq_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
```

```
vgg16 (Model)                (None, 5, 5, 512)         14714688
_________________________________________________________________
global_average_pooling2d (Gl (None, 512)               0
_________________________________________________________________
dense (Dense)                (None, 64)                32832
_________________________________________________________________
dropout (Dropout)            (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 65
=================================================================
Total params: 14,747,585
Trainable params: 32,897
Non-trainable params: 14,714,688
_________________________________________________________________
```

1.6.2 Using the Functional model API

We use Keras' functional API to define the vgg16 output as input into a new set of fully-connected layers like so:

[23]:
```python
#Adding custom Layers
x = vgg16.output
x = GlobalAveragePooling2D()(x)
x = Dense(64, activation='relu')(x)
x = Dropout(0.5)(x)
predictions = Dense(1, activation='sigmoid')(x)
```

We define a new model in terms of inputs and output, and proceed from there on as before:

[24]:
```python
transfer_model = Model(inputs = vgg16.input,
                       outputs = predictions)
```

[25]:
```python
transfer_model.compile(loss = tf.keras.losses.
 ↪BinaryCrossentropy(from_logits=True),
                       optimizer = 'Adam',
                       metrics=["accuracy"])
```

[26]:
```python
transfer_model.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 160, 160, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 160, 160, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 160, 160, 64)      36928
```

```
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 80, 80, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 80, 80, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 80, 80, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 40, 40, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 40, 40, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 40, 40, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 40, 40, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 20, 20, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 20, 20, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 20, 20, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 20, 20, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 10, 10, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 5, 5, 512)         0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 512)               0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                32832
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 65
=================================================================
Total params: 14,747,585
Trainable params: 32,897
Non-trainable params: 14,714,688
_________________________________________________________________
```

1.6.3 Compute baseline metrics

[27]:
```
initial_epochs = 10
validation_steps=20

initial_loss, initial_accuracy = transfer_model.evaluate(validation_batches,␣
↪steps = validation_steps)
```

```
20/20 [==============================] - 1s 39ms/step - loss: 0.7047 - accuracy:
0.5125
```

[28]:
```
print(f'Initial loss: {initial_loss:.2f} | initial_accuracy accuracy:␣
↪{initial_accuracy:.2%}')
```

```
Initial loss: 0.70 | initial_accuracy accuracy: 51.25%
```

1.7 Train VGG16 transfer model

[29]:
```
history = transfer_model.fit(train_batches,
                             epochs=initial_epochs,
                             validation_data=validation_batches)
```

```
Epoch 1/10
582/582 [==============================] - 66s 114ms/step - loss: 0.5639 -
accuracy: 0.8729 - val_loss: 0.5465 - val_accuracy: 0.9371
Epoch 2/10
582/582 [==============================] - 57s 97ms/step - loss: 0.5384 -
accuracy: 0.9260 - val_loss: 0.5424 - val_accuracy: 0.9409
Epoch 3/10
582/582 [==============================] - 53s 92ms/step - loss: 0.5346 -
accuracy: 0.9323 - val_loss: 0.5399 - val_accuracy: 0.9362
Epoch 4/10
582/582 [==============================] - 51s 87ms/step - loss: 0.5331 -
accuracy: 0.9359 - val_loss: 0.5394 - val_accuracy: 0.9444
Epoch 5/10
582/582 [==============================] - 48s 82ms/step - loss: 0.5316 -
accuracy: 0.9378 - val_loss: 0.5388 - val_accuracy: 0.9345
Epoch 6/10
582/582 [==============================] - 48s 82ms/step - loss: 0.5308 -
accuracy: 0.9397 - val_loss: 0.5380 - val_accuracy: 0.9401
Epoch 7/10
582/582 [==============================] - 60s 104ms/step - loss: 0.5305 -
accuracy: 0.9399 - val_loss: 0.5391 - val_accuracy: 0.9431
Epoch 8/10
582/582 [==============================] - 47s 81ms/step - loss: 0.5301 -
accuracy: 0.9400 - val_loss: 0.5384 - val_accuracy: 0.9435
Epoch 9/10
582/582 [==============================] - 60s 103ms/step - loss: 0.5293 -
```

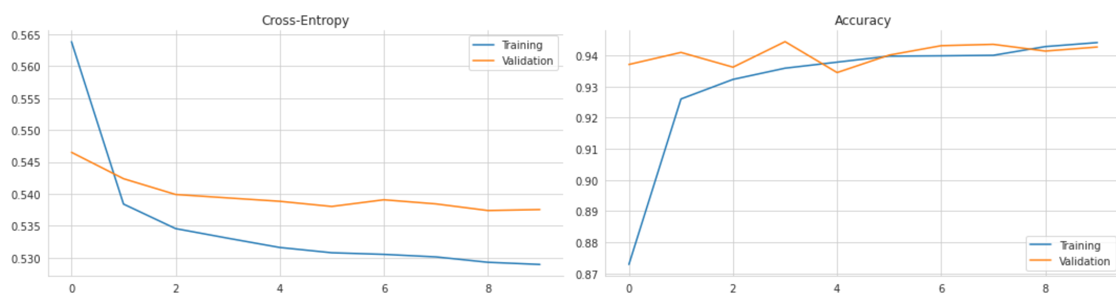
```
accuracy: 0.9428 - val_loss: 0.5374 - val_accuracy: 0.9414
Epoch 10/10
582/582 [==============================] - 58s 100ms/step - loss: 0.5290 -
accuracy: 0.9441 - val_loss: 0.5376 - val_accuracy: 0.9427
```

1.7.1 Plot Learning Curves

[30]:
```
def plot_learning_curves(df):
    fig, axes = plt.subplots(ncols=2, figsize=(15, 4))
    df[['loss', 'val_loss']].plot(ax=axes[0], title='Cross-Entropy')
    df[['accuracy', 'val_accuracy']].plot(ax=axes[1], title='Accuracy')
    for ax in axes:
        ax.legend(['Training', 'Validation'])
    sns.despine()
    fig.tight_layout();
```

[31]:
```
metrics = pd.DataFrame(history.history)
```

[32]:
```
plot_learning_curves(metrics)
```



1.8 Fine-tune VGG16 weights

1.8.1 Unfreeze selected layers

[33]:
```
vgg16.trainable = True
```

How many layers are in the base model:

[34]:
```
f'Number of layers in the base model: {len(vgg16.layers)}'
```

[34]: 'Number of layers in the base model: 19'

[35]:
```
# Fine-tune from this layer onwards
start_fine_tuning_at = 12

# Freeze all the layers before the `fine_tune_at` layer
```

```
for layer in vgg16.layers[:start_fine_tuning_at]:
    layer.trainable =  False
```

[36]:
```
base_learning_rate = 0.0001
transfer_model.compile(
    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
    optimizer=tf.keras.optimizers.RMSprop(lr=base_learning_rate / 10),
    metrics=['accuracy'])
```

1.8.2 Define callbacks

[37]:
```
early_stopping = EarlyStopping(monitor='val_accuracy', patience=10)
```

[38]:
```
transfer_model.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 160, 160, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 160, 160, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 160, 160, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 80, 80, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 80, 80, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 80, 80, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 40, 40, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 40, 40, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 40, 40, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 40, 40, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 20, 20, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 20, 20, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 20, 20, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 20, 20, 512)       2359808
_________________________________________________________________
```

```
block4_pool (MaxPooling2D)   (None, 10, 10, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 10, 10, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 5, 5, 512)         0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 512)               0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                32832
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 65
=================================================================
Total params: 14,747,585
Trainable params: 11,831,937
Non-trainable params: 2,915,648
_________________________________________________________________
```

1.8.3 Continue Training

And now we proceed to train the model:

[39]:
```
fine_tune_epochs = 50
total_epochs = initial_epochs + fine_tune_epochs

history_fine_tune = transfer_model.fit(train_batches,
                                       epochs=total_epochs,
                                       initial_epoch=history.epoch[-1],
                                       validation_data=validation_batches,
                                       callbacks=[early_stopping])
```

```
Epoch 10/60
582/582 [==============================] - 52s 90ms/step - loss: 0.5276 -
accuracy: 0.9480 - val_loss: 0.5346 - val_accuracy: 0.9414
Epoch 11/60
582/582 [==============================] - 52s 90ms/step - loss: 0.5195 -
accuracy: 0.9660 - val_loss: 0.5320 - val_accuracy: 0.9453
Epoch 12/60
582/582 [==============================] - 53s 91ms/step - loss: 0.5162 -
accuracy: 0.9723 - val_loss: 0.5247 - val_accuracy: 0.9711
Epoch 13/60
582/582 [==============================] - 53s 90ms/step - loss: 0.5136 -
accuracy: 0.9785 - val_loss: 0.5233 - val_accuracy: 0.9746
```

```
Epoch 14/60
582/582 [==============================] - 53s 91ms/step - loss: 0.5114 -
accuracy: 0.9834 - val_loss: 0.5245 - val_accuracy: 0.9690
Epoch 15/60
582/582 [==============================] - 52s 89ms/step - loss: 0.5094 -
accuracy: 0.9872 - val_loss: 0.5234 - val_accuracy: 0.9763
Epoch 16/60
582/582 [==============================] - 52s 89ms/step - loss: 0.5085 -
accuracy: 0.9895 - val_loss: 0.5225 - val_accuracy: 0.9750
Epoch 17/60
582/582 [==============================] - 52s 90ms/step - loss: 0.5081 -
accuracy: 0.9907 - val_loss: 0.5236 - val_accuracy: 0.9750
Epoch 18/60
582/582 [==============================] - 53s 91ms/step - loss: 0.5071 -
accuracy: 0.9926 - val_loss: 0.5227 - val_accuracy: 0.9772
Epoch 19/60
582/582 [==============================] - 52s 90ms/step - loss: 0.5070 -
accuracy: 0.9926 - val_loss: 0.5222 - val_accuracy: 0.9746
Epoch 20/60
582/582 [==============================] - 53s 91ms/step - loss: 0.5064 -
accuracy: 0.9937 - val_loss: 0.5220 - val_accuracy: 0.9797
Epoch 21/60
582/582 [==============================] - 53s 91ms/step - loss: 0.5060 -
accuracy: 0.9946 - val_loss: 0.5220 - val_accuracy: 0.9750
Epoch 22/60
582/582 [==============================] - 52s 90ms/step - loss: 0.5057 -
accuracy: 0.9953 - val_loss: 0.5253 - val_accuracy: 0.9741
Epoch 23/60
582/582 [==============================] - 52s 90ms/step - loss: 0.5057 -
accuracy: 0.9953 - val_loss: 0.5233 - val_accuracy: 0.9772
Epoch 24/60
582/582 [==============================] - 55s 95ms/step - loss: 0.5054 -
accuracy: 0.9959 - val_loss: 0.5308 - val_accuracy: 0.9672
Epoch 25/60
582/582 [==============================] - 52s 90ms/step - loss: 0.5056 -
accuracy: 0.9955 - val_loss: 0.5220 - val_accuracy: 0.9776
Epoch 26/60
582/582 [==============================] - 54s 94ms/step - loss: 0.5054 -
accuracy: 0.9960 - val_loss: 0.5222 - val_accuracy: 0.9763
Epoch 27/60
582/582 [==============================] - 54s 93ms/step - loss: 0.5054 -
accuracy: 0.9959 - val_loss: 0.5252 - val_accuracy: 0.9754
Epoch 28/60
582/582 [==============================] - 54s 92ms/step - loss: 0.5053 -
accuracy: 0.9961 - val_loss: 0.5263 - val_accuracy: 0.9737
Epoch 29/60
582/582 [==============================] - 55s 94ms/step - loss: 0.5050 -
accuracy: 0.9967 - val_loss: 0.5219 - val_accuracy: 0.9789
```

```
Epoch 30/60
582/582 [==============================] - 53s 92ms/step - loss: 0.5050 -
accuracy: 0.9966 - val_loss: 0.5227 - val_accuracy: 0.9763
```

[40]:
```
metrics_tuned = metrics.append(pd.DataFrame(history_fine_tune.history),␣
↪ignore_index=True)
```

[41]:
```
fig, axes = plt.subplots(ncols=2, figsize=(15, 4))
metrics_tuned[['loss', 'val_loss']].plot(ax=axes[1], title='Cross-Entropy Loss')
metrics_tuned[['accuracy', 'val_accuracy']].plot(ax=axes[0], title=f'Accuracy␣
↪(Best: {metrics_tuned.val_accuracy.max():.2%})')
axes[0].yaxis.set_major_formatter(FuncFormatter(lambda y, _: '{:.0%}'.
↪format(y)))
axes[0].set_ylabel('Accuracy')
axes[1].set_ylabel('Loss')
for ax in axes:
    ax.axvline(10, ls='--', lw=1, c='k')
    ax.legend(['Training', 'Validation', 'Start Fine Tuning'])
    ax.set_xlabel('Epoch')
sns.despine()
fig.tight_layout()
fig.savefig(results_path / 'transfer_learning');
```