```
In [ ]:
        # Install TensorFlow
        # !pip install -q tensorflow-qpu==2.0.0-beta1
          %tensorflow_version 2.x # Colab only.
         except Exception:
           pass
         import tensorflow as tf
         print(tf.__version__)
        `%tensorflow_version` only switches the major version: 1.x or 2.x.
        You set: `2.x # Colab only.`. This will be interpreted as: `2.x`.
        TensorFlow 2.x selected.
        2.2.0-rc2
In [ ]:
        # additional imports
         import numpy as np
         import matplotlib.pyplot as plt
         from tensorflow.keras.layers import Input, Conv2D, Dense, Flatten, Dropout, GlobalMaxPo
         from tensorflow.keras.models import Model
In [ ]:
         # Load in the data
         cifar10 = tf.keras.datasets.cifar10
         (x_train, y_train), (x_test, y_test) = cifar10.load_data()
         x_train, x_test = x_train / 255.0, x_test / 255.0
        y_train, y_test = y_train.flatten(), y_test.flatten()
         print("x_train.shape:", x_train.shape)
         print("y_train.shape", y_train.shape)
        Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
        x_train.shape: (50000, 32, 32, 3)
        y_train.shape (50000,)
In [ ]:
        # number of classes
        K = len(set(y_train))
         print("number of classes:", K)
        number of classes: 10
In [ ]:
         # Build the model using the functional API
         i = Input(shape=x_train[0].shape)
         \# x = Conv2D(32, (3, 3), strides=2, activation='relu')(i)
         \# x = Conv2D(64, (3, 3), strides=2, activation='relu')(x)
        \# x = Conv2D(128, (3, 3), strides=2, activation='relu')(x)
         x = Conv2D(32, (3, 3), activation='relu', padding='same')(i)
         x = BatchNormalization()(x)
         x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
         x = BatchNormalization()(x)
        x = MaxPooling2D((2, 2))(x)
```

x = Dropout(0.2)(x)

```
x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
         x = BatchNormalization()(x)
         x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
         x = BatchNormalization()(x)
         x = MaxPooling2D((2, 2))(x)
         \# x = Dropout(0.2)(x)
         x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)
         x = BatchNormalization()(x)
         x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)
         x = BatchNormalization()(x)
         x = MaxPooling2D((2, 2))(x)
         \# x = Dropout(0.2)(x)
         \# x = GlobalMaxPooling2D()(x)
         x = Flatten()(x)
         x = Dropout(0.2)(x)
         x = Dense(1024, activation='relu')(x)
         x = Dropout(0.2)(x)
         x = Dense(K, activation='softmax')(x)
         model = Model(i, x)
In [ ]:
         # Compile
         # Note: make sure you are using the GPU for this!
         model.compile(optimizer='adam',
                      loss='sparse_categorical_crossentropy',
                      metrics=['accuracy'])
In [ ]:
         r = model.fit(x_train, y_train, validation_data=(x_test, y_test), epochs=50)
        Epoch 1/50
        KevboardInterrupt
                                                Traceback (most recent call last)
        <ipython-input-7-8848f77f4588> in <module>()
        ----> 1 r = model.fit(x_train, y_train, validation_data=(x_test, y_test), epochs=50)
        /usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/engine/training.py in _me
        thod_wrapper(self, *args, **kwargs)
             64
                 def _method_wrapper(self, *args, **kwargs):
             65
                   if not self._in_multi_worker_mode(): # pylint: disable=protected-access
        ---> 66
                     return method(self, *args, **kwargs)
             67
                   # Running inside `run distribute coordinator` already.
        /usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/engine/training.py in fit
        (self, x, y, batch_size, epochs, verbose, callbacks, validation_split, validation_data,
        shuffle, class weight, sample weight, initial epoch, steps per epoch, validation steps,
        validation_batch_size, validation_freq, max_queue_size, workers, use_multiprocessing, **
        kwargs)
            790
                               context.async_wait()
            791
                             logs = tmp logs # No error, now safe to assign to logs.
        --> 792
                             callbacks.on_train_batch_end(step, logs)
            793
                       epoch_logs = copy.copy(logs)
            794
```

/usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/callbacks.py in on_train_

```
batch_end(self, batch, logs)
    387
   388
            if self._should_call_train_batch_hooks:
--> 389
              logs = self._process_logs(logs)
              self. call batch hook(ModeKeys.TRAIN, 'end', batch, logs=logs)
   390
    391
/usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/callbacks.py in process
logs(self, logs)
            """Turns tensors into numpy arrays or Python scalars."""
   263
            if logs:
   264
--> 265
             return tf_utils.to_numpy_or_python_type(logs)
   266
            return {}
    267
/usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/utils/tf_utils.py in to_n
umpy_or_python_type(tensors)
   521
            return t # Don't turn ragged or sparse tensors to NumPy.
   522
--> 523
          return nest.map_structure(_to_single_numpy_or_python_type, tensors)
    524
/usr/local/lib/python3.6/dist-packages/tensorflow/python/util/nest.py in map_structure(f
unc, *structure, **kwargs)
   615
          return pack_sequence_as(
   616
              structure[0], [func(*x) for x in entries],
--> 617
   618
              expand composites=expand composites)
    619
/usr/local/lib/python3.6/dist-packages/tensorflow/python/util/nest.py in <listcomp>(.0)
   615
   616
          return pack sequence as(
--> 617
              structure[0], [func(*x) for x in entries],
   618
              expand_composites=expand_composites)
   619
/usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/utils/tf_utils.py in _to_
single_numpy_or_python_type(t)
   517
          def _to_single_numpy_or_python_type(t):
   518
            if isinstance(t, ops.Tensor):
--> 519
              x = t.numpy()
              return x.item() if np.ndim(x) == 0 else x
   520
   521
            return t # Don't turn ragged or sparse tensors to NumPy.
/usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/ops.py in numpy(self)
   959
   960
            # TODO(slebedev): Consider avoiding a copy for non-CPU or remote tensors.
--> 961
            maybe_arr = self._numpy() # pylint: disable=protected-access
            return maybe_arr.copy() if isinstance(maybe_arr, np.ndarray) else maybe_arr
   962
   963
/usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/ops.py in _numpy(sel
f)
   925
            # pylint: disable=protected-access
   926
            try:
--> 927
              return self._numpy_internal()
   928
            except core. NotOkStatusException as e:
   929
              six.raise_from(core._status_to_exception(e.code, e.message), None)
KeyboardInterrupt:
# Fit with data augmentation
# Note: if you run this AFTER calling the previous model.fit(), it will CONTINUE traini
```

In []:

```
batch_size = 32
data_generator = tf.keras.preprocessing.image.ImageDataGenerator(width_shift_range=0.1,
train_generator = data_generator.flow(x_train, y_train, batch_size)
steps_per_epoch = x_train.shape[0] // batch_size
r = model.fit(train_generator, validation_data=(x_test, y_test), steps_per_epoch=steps_
```

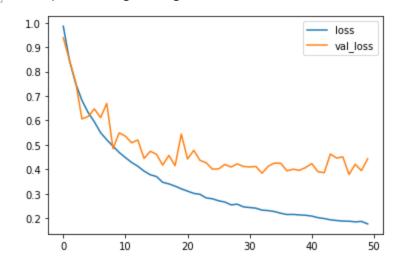
```
6597 - val_loss: 0.9380 - val_accuracy: 0.6898
Epoch 2/50
7101 - val_loss: 0.8461 - val_accuracy: 0.7158
Epoch 3/50
7444 - val_loss: 0.7562 - val_accuracy: 0.7485
Epoch 4/50
7695 - val_loss: 0.6062 - val_accuracy: 0.7959
Epoch 5/50
7856 - val loss: 0.6161 - val accuracy: 0.7971
7997 - val_loss: 0.6473 - val_accuracy: 0.7832
Epoch 7/50
8109 - val_loss: 0.6116 - val_accuracy: 0.8007
Epoch 8/50
8227 - val loss: 0.6694 - val accuracy: 0.7861
Epoch 9/50
8300 - val_loss: 0.4850 - val_accuracy: 0.8358
Epoch 10/50
8407 - val_loss: 0.5492 - val_accuracy: 0.8174
Epoch 11/50
8479 - val_loss: 0.5357 - val_accuracy: 0.8212
Epoch 12/50
8523 - val_loss: 0.5085 - val_accuracy: 0.8319
Epoch 13/50
8577 - val loss: 0.5201 - val accuracy: 0.8308
Epoch 14/50
8662 - val loss: 0.4446 - val accuracy: 0.8510
Epoch 15/50
8694 - val_loss: 0.4738 - val_accuracy: 0.8506
Epoch 16/50
8721 - val_loss: 0.4617 - val_accuracy: 0.8504
Epoch 17/50
8812 - val_loss: 0.4172 - val_accuracy: 0.8627
Epoch 18/50
8818 - val_loss: 0.4572 - val_accuracy: 0.8587
Epoch 19/50
8868 - val loss: 0.4150 - val accuracy: 0.8654
Epoch 20/50
```

```
8880 - val_loss: 0.5443 - val_accuracy: 0.8273
Epoch 21/50
8919 - val loss: 0.4421 - val accuracy: 0.8605
8964 - val loss: 0.4778 - val accuracy: 0.8537
Epoch 23/50
8975 - val_loss: 0.4370 - val_accuracy: 0.8621
Epoch 24/50
9023 - val_loss: 0.4270 - val_accuracy: 0.8676
Epoch 25/50
9035 - val_loss: 0.4009 - val_accuracy: 0.8748
Epoch 26/50
9069 - val_loss: 0.4017 - val_accuracy: 0.8719
Epoch 27/50
9080 - val_loss: 0.4199 - val_accuracy: 0.8669
Epoch 28/50
9121 - val loss: 0.4094 - val accuracy: 0.8703
Epoch 29/50
9110 - val loss: 0.4227 - val accuracy: 0.8698
Epoch 30/50
9141 - val loss: 0.4117 - val accuracy: 0.8649
Epoch 31/50
9157 - val_loss: 0.4096 - val_accuracy: 0.8758
Epoch 32/50
9159 - val_loss: 0.4118 - val_accuracy: 0.8705
Epoch 33/50
9194 - val_loss: 0.3841 - val_accuracy: 0.8764
Epoch 34/50
9201 - val_loss: 0.4127 - val_accuracy: 0.8708
Epoch 35/50
9209 - val_loss: 0.4259 - val_accuracy: 0.8762
Epoch 36/50
9241 - val_loss: 0.4246 - val_accuracy: 0.8769
Epoch 37/50
9251 - val loss: 0.3939 - val accuracy: 0.8797
Epoch 38/50
9261 - val loss: 0.4005 - val accuracy: 0.8790
Epoch 39/50
9268 - val_loss: 0.3959 - val_accuracy: 0.8773
Epoch 40/50
9263 - val_loss: 0.4072 - val_accuracy: 0.8742
Epoch 41/50
9277 - val_loss: 0.4234 - val_accuracy: 0.8769
Epoch 42/50
```

```
9310 - val_loss: 0.3904 - val_accuracy: 0.8812
   Epoch 43/50
   9311 - val loss: 0.3859 - val accuracy: 0.8806
   Epoch 44/50
   9341 - val_loss: 0.4627 - val_accuracy: 0.8703
   Epoch 45/50
   9342 - val_loss: 0.4460 - val_accuracy: 0.8646
   Epoch 46/50
   9341 - val_loss: 0.4511 - val_accuracy: 0.8658
   Epoch 47/50
   9344 - val_loss: 0.3790 - val_accuracy: 0.8831
   Epoch 48/50
   9366 - val_loss: 0.4208 - val_accuracy: 0.8770
   Epoch 49/50
   9364 - val_loss: 0.3946 - val_accuracy: 0.8841
   Epoch 50/50
   9397 - val_loss: 0.4432 - val_accuracy: 0.8781
In [ ]:
    # Plot loss per iteration
    import matplotlib.pyplot as plt
    plt.plot(r.history['loss'], label='loss')
```

Out[]: <matplotlib.legend.Legend at 0x7f1d5a2856d8>

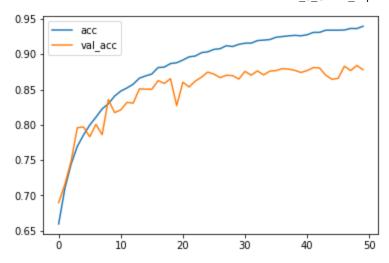
plt.legend()



plt.plot(r.history['val_loss'], label='val_loss')

```
# Plot accuracy per iteration
plt.plot(r.history['accuracy'], label='acc')
plt.plot(r.history['val_accuracy'], label='val_acc')
plt.legend()
```

Out[]: <matplotlib.legend.Legend at 0x7f1d5a26ada0>

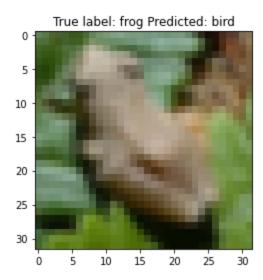


```
In [ ]:
         # Plot confusion matrix
         from sklearn.metrics import confusion matrix
         import itertools
         def plot_confusion_matrix(cm, classes,
                                    normalize=False,
                                    title='Confusion matrix',
                                    cmap=plt.cm.Blues):
           This function prints and plots the confusion matrix.
           Normalization can be applied by setting `normalize=True`.
           if normalize:
               cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
               print("Normalized confusion matrix")
           else:
               print('Confusion matrix, without normalization')
           print(cm)
           plt.imshow(cm, interpolation='nearest', cmap=cmap)
           plt.title(title)
           plt.colorbar()
           tick_marks = np.arange(len(classes))
           plt.xticks(tick_marks, classes, rotation=45)
           plt.yticks(tick_marks, classes)
           fmt = '.2f' if normalize else 'd'
           thresh = cm.max() / 2.
           for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
               plt.text(j, i, format(cm[i, j], fmt),
                        horizontalalignment="center",
                        color="white" if cm[i, j] > thresh else "black")
           plt.tight layout()
           plt.ylabel('True label')
           plt.xlabel('Predicted label')
           plt.show()
         p_test = model.predict(x_test).argmax(axis=1)
         cm = confusion_matrix(y_test, p_test)
         plot confusion matrix(cm, list(range(10)))
```

```
Confusion matrix, without normalization
[[908 14
             12
                   2
                        1
                                  2
                                       2
                                                26]
    5 957
              0
                   0
                        0
                                  3
                                            4
                                                30]
                             1
                                       0
                                            7
   42
         4 817
                  18
                       28
                                      11
                            18
                                 43
                                                12]
   22
        18
             27 742
                       29
                            62
                                 48
                                      19
                                           13
                                                201
   16
         2
             39
                  22 847
                            16
                                 34
                                      15
                                            5
                                                 4]
    5
        10
             22
                       23 790
                                 21
                                      23
                                            4
                                                 8]
                  94
    4
                                                 3]
         2
             16
                  18
                        4
                             2 946
                                       1
                                            4
   15
              6
                  15
                       27
                                  5 908
                                            6
                                                 7]
                             6
   37
        12
                   3
                        0
                                  1
                                       2 921
                                                23]
              1
                             0
        37
                                            4 945]]
    9
                        1
                             1
                                  2
                                       1
                Confusion matrix
     908 14
                          0
                                  2
                                      33
                                          26
                                      4
                                                    800
      42
             817
                 18
                     28
                         18
                             43 11
                                      7
                                          12
  2
                      29
                          62 48 19
                                    13
      22
          18
              27
                  742
                                          20
                                                    600
Fue label
      16
                  22
                     847
                          16
                              34
  4
      5
          10
              22
                  94
                     23
                         790
                              21
                                 23
                                      4
                                          8
  5
                                                    400
              16
                  18
                      4
                          2
                             946
  6
      15
          5
                                 908
                                      6
                                          7
              6
                 15
                     27
                          6
                              5
  7
                                                    200
         12
              1
                  3
                          0
                              1
                                          23
      37
                                   2
                                      921
  8
                                          945
          37
                          5
                                      ዔ
                                          9
      0
                              6
                  Predicted label
```

```
In []: # label mapping
    labels = '''airplane
    automobile
    bird
    cat
    deer
    dog
    frog
    horse
    ship
    truck'''.split()
```

```
In [ ]:
# Show some misclassified examples
misclassified_idx = np.where(p_test != y_test)[0]
i = np.random.choice(misclassified_idx)
plt.imshow(x_test[i], cmap='gray')
plt.title("True label: %s Predicted: %s" % (labels[y_test[i]], labels[p_test[i]]));
```



In []:

Now that the model is so large, it's useful to summarize it
model.summary()

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 32, 32, 3)]	0
conv2d (Conv2D)	(None, 32, 32, 32)	896
batch_normalization (BatchNo	(None, 32, 32, 32)	128
conv2d_1 (Conv2D)	(None, 32, 32, 32)	9248
batch_normalization_1 (Batch	(None, 32, 32, 32)	128
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
conv2d_2 (Conv2D)	(None, 16, 16, 64)	18496
batch_normalization_2 (Batch	(None, 16, 16, 64)	256
conv2d_3 (Conv2D)	(None, 16, 16, 64)	36928
batch_normalization_3 (Batch	(None, 16, 16, 64)	256
max_pooling2d_1 (MaxPooling2	(None, 8, 8, 64)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	73856
batch_normalization_4 (Batch	(None, 8, 8, 128)	512
conv2d_5 (Conv2D)	(None, 8, 8, 128)	147584
batch_normalization_5 (Batch	(None, 8, 8, 128)	512
max_pooling2d_2 (MaxPooling2	(None, 4, 4, 128)	0
flatten (Flatten)	(None, 2048)	0
dropout (Dropout)	(None, 2048)	0
dense (Dense)	(None, 1024)	2098176

dropout_1 (Dropout)

(None, 1024)

0

dense_1 (Dense)

(None, 10)

10250

Total params: 2,397,226 Trainable params: 2,396,330 Non-trainable params: 896