



Introduction

TensorFlow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks.

It is used for both research and production at Google.

TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache 2.0 open-source license on November 9, 2015.

Frameworks



TensorFlow is Google Brain's second-generation system. Version 1.0.0 was released on February 11, 2017. While the reference implementation runs on single devices, TensorFlow can run on multiple CPUs and GPUs (with optional CUDA and SYCL extensions for general-purpose computing on graphics processing units). TensorFlow is available on 64-bit Linux, macOS, Windows, and mobile computing platforms including Android and iOS.

Its flexible architecture allows for the easy deployment of computation across a variety of platforms (CPUs, GPUs, TPUs), and from desktops to clusters of servers to mobile and edge devices.

TensorFlow computations are expressed as stateful dataflow graphs. The name TensorFlow derives from the operations that such neural networks perform on multidimensional data arrays, which are referred to as tensors. During the Google I/O Conference in June 2016, Jeff Dean stated that 1,500 repositories on GitHub mentioned TensorFlow, of which only 5 were from Google.

In May 2017, Google announced a software stack specifically for mobile development, TensorFlow Lite. In January 2019, TensorFlow team released a developer preview of the mobile GPU inference engine with OpenGL ES 3.1 Compute Shaders on Android devices and Metal Compute Shaders on iOS devices.

Project Process

I will be using transfer learning, which means starting with a model that has been already trained on another problem and retrain it on a similar problem. Deep learning from scratch can take days, but transfer learning can be done in short order.

Going to use a model trained on the ImageNet Large Visual Recognition Challenge dataset. These models can differentiate between 1,000 different classes, like Dalmatian or dishwasher. You will have a choice of model architectures, so you can determine the right tradeoff between speed, size and accuracy for your problem.

We will use this same model, but retrain it to tell apart a small number of classes based on our own examples.

IMPORT PACKAGES

```
In [1]: from __future__ import absolute_import
        from __future__ import division
        from __future__ import print_function

        import argparse
        import collections
        from datetime import datetime
        import hashlib
        import os.path
        import random
        import re
        import sys
        import tarfile

        from tensorflow.python.framework import graph_util
        from tensorflow.python.framework import tensor_shape
        from tensorflow.python.platform import gfile
        from tensorflow.python.util import compat

        import numpy as np
        from six.moves import urllib
        import tensorflow as tf

        FLAGS = None
```

PRE-PROCESSING IMAGES

```
In [2]: MAX_NUM_IMAGES_PER_CLASS = 2 ** 27 - 1 # ~134M
```

```
In [3]: def create_image_lists(image_dir, testing_percentage, validation_percentage):
        """Builds a list of training images from the file system.
```

Analyzes the sub folders in the image directory, splits them into stable training, testing, and validation sets, and returns a data structure describing the lists of images for each label and their paths.

Args:

image_dir: String path to a folder containing subfolders of images.

testing_percentage: Integer percentage of the images to reserve for tests.

validation_percentage: Integer percentage of images reserved for validation.

Returns:

A dictionary containing an entry for each label subfolder, with images split

into training, testing, and validation sets within each label.

"""

```
if not gfile.Exists(image_dir):
    tf.logging.error("Image directory '" + image_dir + "' not found.")
```

```
    return None
```

```
result = collections.OrderedDict()
```

```
sub_dirs = []
```

```
    os.path.join(image_dir, item)
```

```
    for item in gfile.ListDirectory(image_dir)
```

```
sub_dirs = sorted(item for item in sub_dirs
```

```
                    if gfile.IsDirectory(item))
```

```
for sub_dir in sub_dirs:
```

```
    extensions = ['jpg', 'jpeg', 'JPG', 'JPEG']
```

```
    file_list = []
```

```
    dir_name = os.path.basename(sub_dir)
```

```
    if dir_name == image_dir:
```

```
        continue
```

```
    tf.logging.info("Looking for images in '" + dir_name + "'")
```

```
    for extension in extensions:
```

```
        file_glob = os.path.join(image_dir, dir_name, '*' + extension)
```

```
n)
```

```
        file_list.extend(gfile.Glob(file_glob))
```

```
    if not file_list:
```

```
        tf.logging.warning('No files found')
```

```
        continue
```

```
    if len(file_list) < 20:
```

```
        tf.logging.warning(
```

```
            'WARNING: Folder has less than 20 images, which may cause issues.')
```

```
    elif len(file_list) > MAX_NUM_IMAGES_PER_CLASS:
```

```
        tf.logging.warning(
```

```
            'WARNING: Folder {} has more than {} images. Some images will '
```

```
            'never be selected.'.format(dir_name, MAX_NUM_IMAGES_PER_CLASS))
```

```
    label_name = re.sub(r'^a-z0-9+', '', dir_name.lower())
```

```
    training_images = []
```

```
    testing_images = []
```

```

validation_images = []
for file_name in file_list:
    base_name = os.path.basename(file_name)
    # We want to ignore anything after '_nohash_' in the file nam
e when
    # deciding which set to put an image in, the data set creator
has a way of
    # grouping photos that are close variations of each other. Fo
r example
    # this is used in the plant disease data set to group multipl
e pictures of
    # the same leaf.
    hash_name = re.sub(r'_nohash_.*$', '', file_name)
    # This looks a bit magical, but we need to decide whether thi
s file should
    # go into the training, testing, or validation sets, and we w
ant to keep
    # existing files in the same set even if more files are subse
quently
    # added.
    # To do that, we need a stable way of deciding based on just
the file name
    # itself, so we do a hash of that and then use that to genera
te a
    # probability value that we use to assign it.
    hash_name_hashed = hashlib.shal(compat.as_bytes(hash_name)).h
exdigest()
    percentage_hash = ((int(hash_name_hashed, 16) %
                        (MAX_NUM_IMAGES_PER_CLASS + 1)) *
                      (100.0 / MAX_NUM_IMAGES_PER_CLASS))
    if percentage_hash < validation_percentage:
        validation_images.append(base_name)
    elif percentage_hash < (testing_percentage + validation_perce
centage):
        testing_images.append(base_name)
    else:
        training_images.append(base_name)
result[label_name] = {
    'dir': dir_name,
    'training': training_images,
    'testing': testing_images,
    'validation': validation_images,
}
return result

```

```

In [4]: def get_image_path(image_lists, label_name, index, image_dir, category):
        """Returns a path to an image for a label at the given index.

        Args:
            image_lists: Dictionary of training images for each label.
            label_name: Label string we want to get an image for.
            index: Int offset of the image we want. This will be moduloed by the
            available number of images for the label, so it can be arbitrarily large.
            image_dir: Root folder string of the subfolders containing the training
            images.
            category: Name string of set to pull images from - training, testing, or
            validation.

        Returns:
            File system path string to an image that meets the requested parameters.

        """
        if label_name not in image_lists:
            tf.logging.fatal('Label does not exist %s.', label_name)
        label_lists = image_lists[label_name]
        if category not in label_lists:
            tf.logging.fatal('Category does not exist %s.', category)
        category_list = label_lists[category]
        if not category_list:
            tf.logging.fatal('Label %s has no images in the category %s.',
                             label_name, category)
        mod_index = index % len(category_list)
        base_name = category_list[mod_index]
        sub_dir = label_lists['dir']
        full_path = os.path.join(image_dir, sub_dir, base_name)
        return full_path

```

```

In [5]: def get_bottleneck_path(image_lists, label_name, index, bottleneck_dir,
                                category, architecture):
    """Returns a path to a bottleneck file for a label at the given
    index.

    Args:
        image_lists: Dictionary of training images for each label.
        label_name: Label string we want to get an image for.
        index: Integer offset of the image we want. This will be modulo
    ed by the
        available number of images for the label, so it can be arbitrar
    ily large.
        bottleneck_dir: Folder string holding cached files of bottlenec
    k values.
        category: Name string of set to pull images from - training, te
    sting, or
        validation.
        architecture: The name of the model architecture.

    Returns:
        File system path string to an image that meets the requested pa
    rameters.
    """
    return get_image_path(image_lists, label_name, index, bottleneck_dir,
                           category) + '_' + architecture + '.txt'

```

```

In [6]: def create_model_graph(model_info, model_dir):
        """Creates a graph from saved GraphDef file and returns a Graph
        object.

        Args:
            model_info: Dictionary containing information about the model a
            rchitecture.

        Returns:
            Graph holding the trained Inception network, and various tensor
            s we'll be
            manipulating.
        """

        with tf.Graph().as_default() as graph:
            model_path = os.path.join(model_dir, model_info['model_file_nam
            e'])
            with gfile.FastGFile(model_path, 'rb') as f:
                graph_def = tf.GraphDef()
                graph_def.ParseFromString(f.read())
                bottleneck_tensor, resized_input_tensor = (tf.import_graph_de
                f(
                    graph_def,
                    name='',
                    return_elements=[
                        model_info['bottleneck_tensor_name'],
                        model_info['resized_input_tensor_name'],
                    ]))
        return graph, bottleneck_tensor, resized_input_tensor

```

```

In [7]: def run_bottleneck_on_image(sess, image_data, image_data_tensor,
                                         decoded_image_tensor, resized_input_ten
sor,
                                         bottleneck_tensor):
    """Runs inference on an image to extract the 'bottleneck' summary
layer.

Args:
    sess: Current active TensorFlow Session.
    image_data: String of raw JPEG data.
    image_data_tensor: Input data layer in the graph.
    decoded_image_tensor: Output of initial image resizing and pre
processing.
    resized_input_tensor: The input node of the recognition graph.
    bottleneck_tensor: Layer before the final softmax.

Returns:
    Numpy array of bottleneck values.
    """
    # First decode the JPEG image, resize it, and rescale the pixel v
alues.
    resized_input_values = sess.run(decoded_image_tensor,
                                     {image_data_tensor: image_data})
    # Then run it through the recognition network.
    bottleneck_values = sess.run(bottleneck_tensor,
                                  {resized_input_tensor: resized_input
_values})
    bottleneck_values = np.squeeze(bottleneck_values)
    return bottleneck_values

```



```
In [8]: def maybe_download_and_extract(data_url):
        """Download and extract model tar file.

        If the pretrained model we're using doesn't already exist, this function
        downloads it from the TensorFlow.org website and unpacks it into
        a directory.

        Args:
            data_url: Web location of the tar file containing the pretrained model.
        """
        dest_directory = "model_dir"
        if not os.path.exists(dest_directory):
            os.makedirs(dest_directory)
        filename = data_url.split('/')[-1]
        filepath = os.path.join(dest_directory, filename)
        if not os.path.exists(filepath):

            def _progress(count, block_size, total_size):
                sys.stdout.write('\r>> Downloading %s %.1f%%' %
                                (filename,
                                 float(count * block_size) / float(total_size) * 100.0))
                sys.stdout.flush()

            filepath, _ = urllib.request.urlretrieve(data_url, filepath, _progress)
            print()
            statinfo = os.stat(filepath)
            tf.logging.info('Successfully downloaded', filename, statinfo.st_size,
                            'bytes.')
            tarfile.open(filepath, 'r:gz').extractall(dest_directory)
```

```
In [9]: def ensure_dir_exists(dir_name):
        """Makes sure the folder exists on disk.

        Args:
            dir_name: Path string to the folder we want to create.
        """
        if not os.path.exists(dir_name):
            os.makedirs(dir_name)

bottleneck_path_2_bottleneck_values = {}
```

```

In [10]: def create_bottleneck_file(bottleneck_path, image_lists, label_name
, index,
                                image_dir, category, sess, jpeg_data_ten
sor,
                                decoded_image_tensor, resized_input_tens
or,
                                bottleneck_tensor):
    """Create a single bottleneck file."""
    tf.logging.info('Creating bottleneck at ' + bottleneck_path)
    image_path = get_image_path(image_lists, label_name, index,
                                image_dir, category)
    if not gfile.Exists(image_path):
        tf.logging.fatal('File does not exist %s', image_path)
    image_data = gfile.GFile(image_path, 'rb').read()
    try:
        bottleneck_values = run_bottleneck_on_image(
            sess, image_data, jpeg_data_tensor, decoded_image_tensor,
            resized_input_tensor, bottleneck_tensor)
    except Exception as e:
        raise RuntimeError('Error during processing file %s (%s)' % (im
age_path,
                                                                    st
r(e)))
    bottleneck_string = ','.join(str(x) for x in bottleneck_values)
    with open(bottleneck_path, 'w') as bottleneck_file:
        bottleneck_file.write(bottleneck_string)

```

```

In [11]: def get_or_create_bottleneck(sess, image_lists, label_name, index,
image_dir,
                                category, bottleneck_dir, jpeg_data_te
nsor,
                                decoded_image_tensor, resized_input_te
nsor,
                                bottleneck_tensor, architecture):
    """Retrieves or calculates bottleneck values for an image.

If a cached version of the bottleneck data exists on-disk, return
that,
otherwise calculate the data and save it to disk for future use.

Args:
    sess: The current active TensorFlow Session.
    image_lists: Dictionary of training images for each label.
    label_name: Label string we want to get an image for.
    index: Integer offset of the image we want. This will be modulo
-ed by the
    available number of images for the label, so it can be arbitrar
ily large.
    image_dir: Root folder string of the subfolders containing the
training
    images.
    category: Name string of which set to pull images from - train
ing, testing,
    or validation.
    bottleneck_dir: Folder string holding cached files of bottlenec
k values.

```

jpeg_data_tensor: The tensor to feed loaded jpeg data into.
decoded_image_tensor: The output of decoding and resizing the image.
resized_input_tensor: The input node of the recognition graph.
bottleneck_tensor: The output tensor for the bottleneck values.
architecture: The name of the model architecture.

Returns:

Numpy array of values produced by the bottleneck layer for the image.

```
"""
label_lists = image_lists[label_name]
sub_dir = label_lists['dir']
sub_dir_path = os.path.join(bottleneck_dir, sub_dir)
ensure_dir_exists(sub_dir_path)
bottleneck_path = get_bottleneck_path(image_lists, label_name, index,
                                      bottleneck_dir, category, architecture)
if not os.path.exists(bottleneck_path):
    create_bottleneck_file(bottleneck_path, image_lists, label_name, index,
                          image_dir, category, sess, jpeg_data_tensor,
                          decoded_image_tensor, resized_input_tensor,
                          bottleneck_tensor)
with open(bottleneck_path, 'r') as bottleneck_file:
    bottleneck_string = bottleneck_file.read()
    did_hit_error = False
    try:
        bottleneck_values = [float(x) for x in bottleneck_string.split(',')]
    except ValueError:
        tf.logging.warning('Invalid float found, recreating bottleneck')
        did_hit_error = True
    if did_hit_error:
        create_bottleneck_file(bottleneck_path, image_lists, label_name, index,
                              image_dir, category, sess, jpeg_data_tensor,
                              decoded_image_tensor, resized_input_tensor,
                              bottleneck_tensor)
    with open(bottleneck_path, 'r') as bottleneck_file:
        bottleneck_string = bottleneck_file.read()
        # Allow exceptions to propagate here, since they shouldn't happen after a
        # fresh creation
        bottleneck_values = [float(x) for x in bottleneck_string.split(',')]
return bottleneck_values
```

```

In [12]: def cache_bottlenecks(sess, image_lists, image_dir, bottleneck_dir,
                                jpeg_data_tensor, decoded_image_tensor,
                                resized_input_tensor, bottleneck_tensor, arch
                                itecture):
    """Ensures all the training, testing, and validation bottlenecks
    are cached.

    Because we're likely to read the same image multiple times (if there are no
    distortions applied during training) it can speed things up a lot if we
    calculate the bottleneck layer values once for each image during
    preprocessing, and then just read those cached values repeatedly
    during training. Here we go through all the images we've found, calculate those
    values, and save them off.

    Args:
        sess: The current active TensorFlow Session.
        image_lists: Dictionary of training images for each label.
        image_dir: Root folder string of the subfolders containing the training
        images.
        bottleneck_dir: Folder string holding cached files of bottleneck
        k values.
        jpeg_data_tensor: Input tensor for jpeg data from file.
        decoded_image_tensor: The output of decoding and resizing the image.
        resized_input_tensor: The input node of the recognition graph.
        bottleneck_tensor: The penultimate output layer of the graph.
        architecture: The name of the model architecture.

    Returns:
        Nothing.
    """
    how_many_bottlenecks = 0
    ensure_dir_exists(bottleneck_dir)
    for label_name, label_lists in image_lists.items():
        for category in ['training', 'testing', 'validation']:
            category_list = label_lists[category]
            for index, unused_base_name in enumerate(category_list):
                get_or_create_bottleneck(
                    sess, image_lists, label_name, index, image_dir, category,
                    bottleneck_dir, jpeg_data_tensor, decoded_image_tensor,
                    resized_input_tensor, bottleneck_tensor, architecture)

            how_many_bottlenecks += 1
            if how_many_bottlenecks % 100 == 0:
                tf.logging.info(
                    str(how_many_bottlenecks) + ' bottleneck files created.')

```

```

In [13]: def get_random_cached_bottlenecks(sess, image_lists, how_many, category,

```

```

        bottleneck_dir, image_dir, jpeg_data_tensor,
        decoded_image_tensor, resized_input_tensor,
        bottleneck_tensor, architecture):
    """Retrieves bottleneck values for cached images.

    If no distortions are being applied, this function can retrieve the
    cached bottleneck values directly from disk for images. It picks a
    random set of images from the specified category.

    Args:
        sess: Current TensorFlow Session.
        image_lists: Dictionary of training images for each label.
        how_many: If positive, a random sample of this size will be chosen.
            If negative, all bottlenecks will be retrieved.
        category: Name string of which set to pull from - training, testing,
            or validation.
        bottleneck_dir: Folder string holding cached files of bottleneck
            values.
        image_dir: Root folder string of the subfolders containing the
            training images.
        jpeg_data_tensor: The layer to feed jpeg image data into.
        decoded_image_tensor: The output of decoding and resizing the image.
        resized_input_tensor: The input node of the recognition graph.
        bottleneck_tensor: The bottleneck output layer of the CNN graph.
        architecture: The name of the model architecture.

    Returns:
        List of bottleneck arrays, their corresponding ground truths, and the
        relevant filenames.
    """
    class_count = len(image_lists.keys())
    bottlenecks = []
    ground_truths = []
    filenames = []
    if how_many >= 0:
        # Retrieve a random sample of bottlenecks.
        for unused_i in range(how_many):
            label_index = random.randrange(class_count)
            label_name = list(image_lists.keys())[label_index]
            image_index = random.randrange(MAX_NUM_IMAGES_PER_CLASS + 1)
            image_name = get_image_path(image_lists, label_name, image_index,
                                         image_dir, category)
            bottleneck = get_or_create_bottleneck(
                sess, image_lists, label_name, image_index, image_dir, category,
                bottleneck_dir, jpeg_data_tensor, decoded_image_tensor,

```

```

        resized_input_tensor, bottleneck_tensor, architecture)
    ground_truth = np.zeros(class_count, dtype=np.float32)
    ground_truth[label_index] = 1.0
    bottlenecks.append(bottleneck)
    ground_truths.append(ground_truth)
    filenames.append(image_name)
else:
    # Retrieve all bottlenecks.
    for label_index, label_name in enumerate(image_lists.keys()):
        for image_index, image_name in enumerate(
            image_lists[label_name][category]):
            image_name = get_image_path(image_lists, label_name, image_
index,
                                     image_dir, category)
            bottleneck = get_or_create_bottleneck(
                sess, image_lists, label_name, image_index, image_dir,
category,
                bottleneck_dir, jpeg_data_tensor, decoded_image_tensor,
                resized_input_tensor, bottleneck_tensor, architecture)
            ground_truth = np.zeros(class_count, dtype=np.float32)
            ground_truth[label_index] = 1.0
            bottlenecks.append(bottleneck)
            ground_truths.append(ground_truth)
            filenames.append(image_name)
    return bottlenecks, ground_truths, filenames

```

In [14]:

```

def get_random_distorted_bottlenecks(
    sess, image_lists, how_many, category, image_dir, input_jpeg_ten
nsor,
    distorted_image, resized_input_tensor, bottleneck_tensor):
    """Retrieves bottleneck values for training images, after distort
ions.

    If we're training with distortions like crops, scales, or flips,
we have to
    recalculate the full model for every image, and so we can't use c
ached
    bottleneck values. Instead we find random images for the requeste
d category,
    run them through the distortion graph, and then the full graph to
get the
    bottleneck results for each.

    Args:
        sess: Current TensorFlow Session.
        image_lists: Dictionary of training images for each label.
        how_many: The integer number of bottleneck values to return.
        category: Name string of which set of images to fetch - trainin
g, testing,
        or validation.
        image_dir: Root folder string of the subfolders containing the
training
        images.
        input_jpeg_tensor: The input layer we feed the image data to.
        distorted_image: The output node of the distortion graph.
        resized_input_tensor: The input node of the recognition graph.
        bottleneck_tensor: The bottleneck output layer of the CNN graph

```

```

•
Returns:
    List of bottleneck arrays and their corresponding ground truths
•
    """
    class_count = len(image_lists.keys())
    bottlenecks = []
    ground_truths = []
    for unused_i in range(how_many):
        label_index = random.randrange(class_count)
        label_name = list(image_lists.keys())[label_index]
        image_index = random.randrange(MAX_NUM_IMAGES_PER_CLASS + 1)
        image_path = get_image_path(image_lists, label_name, image_index,
                                     image_dir,
                                     category)

        if not gfile.Exists(image_path):
            tf.logging.fatal('File does not exist %s', image_path)
        jpeg_data = gfile.GFile(image_path, 'rb').read()
        # Note that we materialize the distorted_image_data as a numpy
        array before
        # sending running inference on the image. This involves 2 memory
        y copies and
        # might be optimized in other implementations.
        distorted_image_data = sess.run(distorted_image,
                                         {input_jpeg_tensor: jpeg_data})
        bottleneck_values = sess.run(bottleneck_tensor,
                                         {resized_input_tensor: distorted_i
image_data})
        bottleneck_values = np.squeeze(bottleneck_values)
        ground_truth = np.zeros(class_count, dtype=np.float32)
        ground_truth[label_index] = 1.0
        bottlenecks.append(bottleneck_values)
        ground_truths.append(ground_truth)
    return bottlenecks, ground_truths

```

```
In [15]: def should_distort_images(flip_left_right, random_crop, random_scale,
                                random_brightness):
    """Whether any distortions are enabled, from the input flags.

    Args:
        flip_left_right: Boolean whether to randomly mirror images horizontally.
        random_crop: Integer percentage setting the total margin used around the
        crop box.
        random_scale: Integer percentage of how much to vary the scale by.
        random_brightness: Integer range to randomly multiply the pixel values by.

    Returns:
        Boolean value indicating whether any distortions should be applied.
    """
    return (flip_left_right or (random_crop != 0) or (random_scale != 0) or
            (random_brightness != 0))
```

```
In [16]: def add_input_distortions(flip_left_right, random_crop, random_scale,
                                random_brightness, input_width, input_height,
                                input_depth, input_mean, input_std):
    """Creates the operations to apply the specified distortions.

    During training it can help to improve the results if we run the images
    through simple distortions like crops, scales, and flips. These reflect the
    kind of variations we expect in the real world, and so can help train the
    model to cope with natural data more effectively. Here we take the supplied
    parameters and construct a network of operations to apply them to an image.

    Cropping
    ~~~~~

    Cropping is done by placing a bounding box at a random position in the full
    image. The cropping parameter controls the size of that box relative to the
    input image. If it's zero, then the box is the same size as the input and no
    cropping is performed. If the value is 50%, then the crop box will be half the
    width and height of the input. In a diagram it looks like this:

    <          width          >
```



```

+-----+
|               |
|   width - crop%   |
|   <       >       |
|   +-----+       |
|   |           |       |
|   |           |       |
|   +-----+       |
|               |
+-----+

```

Scaling

~~~~~

Scaling is a lot like cropping, except that the bounding box is always

centered and its size varies randomly within the given range. For example if

the scale percentage is zero, then the bounding box is the same size as the

input and no scaling is applied. If it's 50%, then the bounding box will be in

a random range between half the width and height and full size.

### Args:

*flip\_left\_right*: Boolean whether to randomly mirror images horizontally.

*random\_crop*: Integer percentage setting the total margin used around the

crop box.

*random\_scale*: Integer percentage of how much to vary the scale by.

*random\_brightness*: Integer range to randomly multiply the pixel values by.

*graph*.

*input\_width*: Horizontal size of expected input image to model.

*input\_height*: Vertical size of expected input image to model.

*input\_depth*: How many channels the expected input image should have.

*input\_mean*: Pixel value that should be zero in the image for the graph.

*input\_std*: How much to divide the pixel values by before recognition.

### Returns:

The jpeg input layer and the distorted result tensor.

"""

```

jpeg_data = tf.placeholder(tf.string, name='DistortJPGInput')
decoded_image = tf.image.decode_jpeg(jpeg_data, channels=input_depth)
decoded_image_as_float = tf.cast(decoded_image, dtype=tf.float32)
decoded_image_4d = tf.expand_dims(decoded_image_as_float, 0)
margin_scale = 1.0 + (random_crop / 100.0)
resize_scale = 1.0 + (random_scale / 100.0)

```

```

margin_scale_value = tf.constant(margin_scale)
resize_scale_value = tf.random_uniform(tensor_shape.scalar(),
                                       minval=1.0,
                                       maxval=resize_scale)
scale_value = tf.multiply(margin_scale_value, resize_scale_value)
precrop_width = tf.multiply(scale_value, input_width)
precrop_height = tf.multiply(scale_value, input_height)
precrop_shape = tf.stack([precrop_height, precrop_width])
precrop_shape_as_int = tf.cast(precrop_shape, dtype=tf.int32)
precropped_image = tf.image.resize_bilinear(decoded_image_4d,
                                           precrop_shape_as_int)
precropped_image_3d = tf.squeeze(precropped_image, squeeze_dims=[
0])
cropped_image = tf.random_crop(precropped_image_3d,
                              [input_height, input_width, input_
depth])
if flip_left_right:
    flipped_image = tf.image.random_flip_left_right(cropped_image)
else:
    flipped_image = cropped_image
brightness_min = 1.0 - (random_brightness / 100.0)
brightness_max = 1.0 + (random_brightness / 100.0)
brightness_value = tf.random_uniform(tensor_shape.scalar(),
                                     minval=brightness_min,
                                     maxval=brightness_max)
brightened_image = tf.multiply(flipped_image, brightness_value)
offset_image = tf.subtract(brightened_image, input_mean)
mul_image = tf.multiply(offset_image, 1.0 / input_std)
distort_result = tf.expand_dims(mul_image, 0, name='DistortResult
')
return jpeg_data, distort_result

```

```

In [17]: def variable_summaries(var):
    """Attach a lot of summaries to a Tensor (for TensorBoard visuali
zation)."""
    with tf.name_scope('summaries'):
        mean = tf.reduce_mean(var)
        tf.summary.scalar('mean', mean)
    with tf.name_scope('stddev'):
        stddev = tf.sqrt(tf.reduce_mean(tf.square(var - mean)))
        tf.summary.scalar('stddev', stddev)
        tf.summary.scalar('max', tf.reduce_max(var))
        tf.summary.scalar('min', tf.reduce_min(var))
        tf.summary.histogram('histogram', var)

```

```

In [18]: def add_final_training_ops(class_count, final_tensor_name, bottlene
ck_tensor,
                                       bottleneck_tensor_size):
    """Adds a new softmax and fully-connected layer for training.

    We need to retrain the top layer to identify our new classes, so
    this function
    adds the right operations to the graph, along with some variables
    to hold the
    weights, and then sets up all the gradients for the backward pass
    .
    """

```

The set up for the softmax and fully-connected layers is based on :

<https://www.tensorflow.org/versions/master/tutorials/mnist/beginners/index.html>

Args:

*class\_count: Integer of how many categories of things we're trying to recognize.*  
*final\_tensor\_name: Name string for the new final node that produces results.*  
*bottleneck\_tensor: The output of the main CNN graph.*  
*bottleneck\_tensor\_size: How many entries in the bottleneck vector.*

Returns:

*The tensors for the training and cross entropy results, and tensors for the bottleneck input and ground truth input.*

```
"""  
with tf.name_scope('input'):  
    bottleneck_input = tf.placeholder_with_default(  
        bottleneck_tensor,  
        shape=[None, bottleneck_tensor_size],  
        name='BottleneckInputPlaceholder')  
  
    ground_truth_input = tf.placeholder(tf.float32,  
                                       [None, class_count],  
                                       name='GroundTruthInput')  
  
    # Organizing the following ops as `final_training_ops` so they're easier  
    # to see in TensorBoard  
    layer_name = 'final_training_ops'  
    with tf.name_scope(layer_name):  
        with tf.name_scope('weights'):  
            initial_value = tf.truncated_normal(  
                [bottleneck_tensor_size, class_count], stddev=0.001)  
  
            layer_weights = tf.Variable(initial_value, name='final_weights')  
  
            variable_summaries(layer_weights)  
            with tf.name_scope('biases'):  
                layer_biases = tf.Variable(tf.zeros([class_count]), name='final_biases')  
  
            variable_summaries(layer_biases)  
            with tf.name_scope('Wx_plus_b'):  
                logits = tf.matmul(bottleneck_input, layer_weights) + layer_biases  
  
            tf.summary.histogram('pre_activations', logits)  
  
            final_tensor = tf.nn.softmax(logits, name=final_tensor_name)  
            tf.summary.histogram('activations', final_tensor)
```

```

with tf.name_scope('cross_entropy'):
    cross_entropy = tf.nn.softmax_cross_entropy_with_logits(
        labels=ground_truth_input, logits=logits)
    with tf.name_scope('total'):
        cross_entropy_mean = tf.reduce_mean(cross_entropy)
tf.summary.scalar('cross_entropy', cross_entropy_mean)

with tf.name_scope('train'):
    optimizer = tf.train.GradientDescentOptimizer(learning_rate)
    train_step = optimizer.minimize(cross_entropy_mean)

return (train_step, cross_entropy_mean, bottleneck_input, ground_
truth_input,
        final_tensor)

```

In [19]:

```

def add_evaluation_step(result_tensor, ground_truth_tensor):
    """Inserts the operations we need to evaluate the accuracy of our
    results.

    Args:
        result_tensor: The new final node that produces results.
        ground_truth_tensor: The node we feed ground truth data
        into.

    Returns:
        Tuple of (evaluation step, prediction).
    """
    with tf.name_scope('accuracy'):
        with tf.name_scope('correct_prediction'):
            prediction = tf.argmax(result_tensor, 1)
            correct_prediction = tf.equal(
                prediction, tf.argmax(ground_truth_tensor, 1))
        with tf.name_scope('accuracy'):
            evaluation_step = tf.reduce_mean(tf.cast(correct_prediction,
tf.float32))
        tf.summary.scalar('accuracy', evaluation_step)
    return evaluation_step, prediction

```

In [20]:

```

def save_graph_to_file(sess, graph, graph_file_name):
    output_graph_def = graph_util.convert_variables_to_constants(
        sess, graph.as_graph_def(), [final_tensor_name])
    with gfile.GFile(graph_file_name, 'wb') as f:
        f.write(output_graph_def.SerializeToString())
    return

```

```
In [21]: def prepare_file_system():
# Setup the directory we'll write summaries to for TensorBoard
summaries_dir = "retrain_logs"
intermediate_store_frequency = 0 # How many steps to store intermediate graph. If "0" then will not store!

if tf.gfile.Exists(summaries_dir):
    tf.gfile.DeleteRecursively(summaries_dir)
tf.gfile.MakeDirs(summaries_dir)

if intermediate_store_frequency > 0:
    ensure_dir_exists(intermediate_output_graphs_dir)
return
```

```
In [22]: def create_model_info(architecture):
"""Given the name of a model architecture, returns information about it.

There are different base image recognition pretrained models that can be
retrained using transfer learning, and this function translates from the name
of a model to the attributes that are needed to download and train with it.

Args:
    architecture: Name of a model architecture.

Returns:
    Dictionary of information about the model, or None if the name isn't
    recognized

Raises:
    ValueError: If architecture name is unknown.
"""
architecture = architecture.lower()
if architecture == 'inception_v3':
    # pylint: disable=line-too-long
    data_url = 'http://download.tensorflow.org/models/image/imagenet/inception-2015-12-05.tgz'
    # pylint: enable=line-too-long
    bottleneck_tensor_name = 'pool_3/_reshape:0'
    bottleneck_tensor_size = 2048
    input_width = 299
    input_height = 299
    input_depth = 3
    resized_input_tensor_name = 'Mul:0'
    model_file_name = 'classify_image_graph_def.pb'
    input_mean = 128
    input_std = 128
elif architecture.startswith('mobilenet_'):
    parts = architecture.split('_')
    if len(parts) != 3 and len(parts) != 4:
        tf.logging.error("Couldn't understand architecture name '%s'"
,

```

```

        architecture)
    return None
version_string = parts[1]
if (version_string != '1.0' and version_string != '0.75' and
    version_string != '0.50' and version_string != '0.25'):
    tf.logging.error(
        """The Mobilenet version should be '1.0', '0.75', '0.50'
, or '0.25',
but found '%s' for architecture '%s'""",
        version_string, architecture)
    return None
size_string = parts[2]
if (size_string != '224' and size_string != '192' and
    size_string != '160' and size_string != '128'):
    tf.logging.error(
        """The Mobilenet input size should be '224', '192', '160'
, or '128',
but found '%s' for architecture '%s'""",
        size_string, architecture)
    return None
if len(parts) == 3:
    is_quantized = False
else:
    if parts[3] != 'quantized':
        tf.logging.error(
            "Couldn't understand architecture suffix '%s' for '%s'"
, parts[3],
            architecture)
        return None
    is_quantized = True
data_url = 'http://download.tensorflow.org/models/mobilenet_v1_
',

data_url += version_string + '_' + size_string + '_frozen.tgz'
bottleneck_tensor_name = 'MobilenetV1/Predictions/Reshape:0'
bottleneck_tensor_size = 1001
input_width = int(size_string)
input_height = int(size_string)
input_depth = 3
resized_input_tensor_name = 'input:0'
if is_quantized:
    model_base_name = 'quantized_graph.pb'
else:
    model_base_name = 'frozen_graph.pb'
model_dir_name = 'mobilenet_v1_' + version_string + '_' + size_
string
model_file_name = os.path.join(model_dir_name, model_base_name)
input_mean = 127.5
input_std = 127.5
else:
    tf.logging.error("Couldn't understand architecture name '%s'",
architecture)
    raise ValueError('Unknown architecture', architecture)

return {
    'data_url': data_url,
    'bottleneck_tensor_name': bottleneck_tensor_name,
    'bottleneck_tensor_size': bottleneck_tensor_size,

```

```

        'input_width': input_width,
        'input_height': input_height,
        'input_depth': input_depth,
        'resized_input_tensor_name': resized_input_tensor_name,
        'model_file_name': model_file_name,
        'input_mean': input_mean,
        'input_std': input_std,
    }

```

```

In [23]: def add_jpeg_decoding(input_width, input_height, input_depth, input
        _mean,
                input_std):
    """Adds operations that perform JPEG decoding and resizing to the
    graph..

    Args:
        input_width: Desired width of the image fed into the recognizer
    graph.
        input_height: Desired width of the image fed into the recognize
    r graph.
        input_depth: Desired channels of the image fed into the recogni
    zer graph.
        input_mean: Pixel value that should be zero in the image for th
    e graph.
        input_std: How much to divide the pixel values by before recogn
    ition.

    Returns:
        Tensors for the node to feed JPEG data into, and the output of
    the
        preprocessing steps.
    """

    jpeg_data = tf.placeholder(tf.string, name='DecodeJPGInput')
    decoded_image = tf.image.decode_jpeg(jpeg_data, channels=input_de
    pth)
    decoded_image_as_float = tf.cast(decoded_image, dtype=tf.float32)
    decoded_image_4d = tf.expand_dims(decoded_image_as_float, 0)
    resize_shape = tf.stack([input_height, input_width])
    resize_shape_as_int = tf.cast(resize_shape, dtype=tf.int32)
    resized_image = tf.image.resize_bilinear(decoded_image_4d,
                                             resize_shape_as_int)
    offset_image = tf.subtract(resized_image, input_mean)
    mul_image = tf.multiply(offset_image, 1.0 / input_std)
    return jpeg_data, mul_image

```

```

In [24]: # Needed to make sure the logging output is visible.
        # See https://github.com/tensorflow/tensorflow/issues/3047
        tf.logging.set_verbosity(tf.logging.INFO)

```

```

In [25]: # Prepare necessary directories that can be used during training
        prepare_file_system()

```

# RETRAINING THE NETWORK

## Configure your MobileNet

MobileNet is a small efficient convolutional neural network. "Convolutional" just means that the same calculations are performed at each location in the image.

The MobileNet is configurable in two ways:

- Input image resolution: 128,160,192, or 224px. Unsurprisingly, feeding in a higher resolution image takes more processing time, but results in better classification accuracy.
- The relative size of the model as a fraction of the largest MobileNet: 1.0, 0.75, 0.50, or 0.25.

I will use image resolution as (h:224px X w:224px) & relative size as 0.5 for this project.

```
In [26]: # Gather information about the model architecture we'll be using.
architecture = "mobilenet_0.50_224"

model_info = create_model_info(architecture)
```

```
In [27]: # Set up the pre-trained graph.
data_url = "../tf_files/Clothes/"
model_dir = "model_dir/"

maybe_download_and_extract(model_info['data_url'])

graph, bottleneck_tensor, resized_image_tensor = (create_model_graph(model_info, model_dir))
```

```
WARNING:tensorflow:From <ipython-input-6-f6601b6ba390>:13: FastGFile.__init__ (from tensorflow.python.platform.gfile) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.gfile.GFile.
```



```
In [28]: # Look at the folder structure, and create lists of all the images.
testing_percentage = 10
validation_percentage = 10
image_dir = "../tf_files/Clothes/"

image_lists = create_image_lists(image_dir, testing_percentage, validation_percentage)
class_count = len(image_lists.keys())

if class_count == 0:
    tf.logging.error('No valid folders of images found at ' + image_dir)

if class_count == 1:
    tf.logging.error('Only one valid folder of images found at ' + image_dir + ' - multiple classes are needed for classification.')

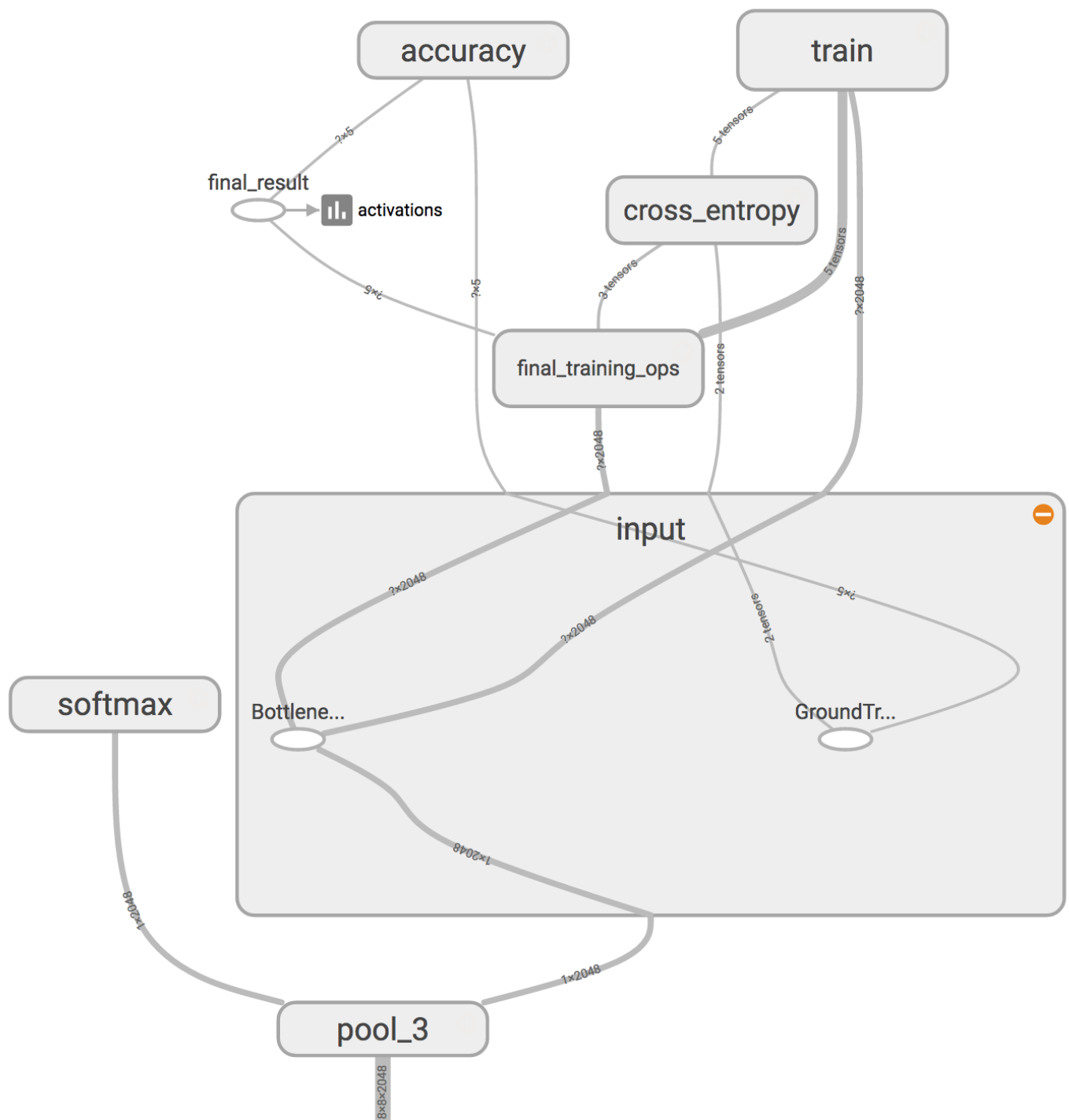
INFO:tensorflow:Looking for images in 'Blazer'
INFO:tensorflow:Looking for images in 'Cap'
INFO:tensorflow:Looking for images in 'Chino'
INFO:tensorflow:Looking for images in 'Denim Shirt'
INFO:tensorflow:Looking for images in 'Dress'
INFO:tensorflow:Looking for images in 'Hoodie'
INFO:tensorflow:Looking for images in 'Jacket'
INFO:tensorflow:Looking for images in 'Jeans'
INFO:tensorflow:Looking for images in 'Kurta'
INFO:tensorflow:Looking for images in 'Leather Jacket'
INFO:tensorflow:Looking for images in 'Polo Shirt'
INFO:tensorflow:Looking for images in 'Shirt'
INFO:tensorflow:Looking for images in 'Shorts'
INFO:tensorflow:Looking for images in 'Suit'
INFO:tensorflow:Looking for images in 'Sweater'
INFO:tensorflow:Looking for images in 'T-Shirt'
```

```
In [29]: # Set parameters for applying any distortions.
do_distort_images = should_distort_images(
    flip_left_right=False,
    random_crop=0,
    random_scale=0,
    random_brightness=0)
```

## Bottlenecks

What's a bottleneck?

These models are made up of many layers stacked on top of each other, a simplified picture of Inception V3 from TensorBoard, is shown above (all the details are available in this paper, with a complete picture on page 6). These layers are pre-trained and are already very valuable at finding and summarizing information that will help classify most images. For this codelab, you are training only the last layer (final\_training\_ops in the figure below). While all the previous layers retain their already-trained state.



In the above figure, the node labeled "softmax", on the left side, is the output layer of the original model. While all the nodes to the right of the "softmax" were added by the retraining script.

```
In [30]: # Hyperparameters
image_dir = "../tf_files/Clothes/"
bottleneck_dir = "bottleneck_dir"
how_many_training_steps = 1000
train_batch_size = 100
validation_batch_size = 100
test_batch_size = 100
eval_step_interval = 10
intermediate_store_frequency = 0
intermediate_output_graphs_dir = "intermediate_graphs"
final_tensor_name="final_result"
learning_rate = 0.01
summaries_dir = "retrain_logs"
```

```

output_labels = 'output_labels.txt'
output_graph = 'output_graph.pb'
print_misclassified_test_images = False

with tf.Session(graph=graph) as sess:
    # Set up the image decoding sub-graph.
    jpeg_data_tensor, decoded_image_tensor = add_jpeg_decoding(
        model_info['input_width'], model_info['input_height'],
        model_info['input_depth'], model_info['input_mean'],
        model_info['input_std'])

    if do_distort_images:
        # We will be applying distortions, so setup the operations we
        'll need.
        (distorted_jpeg_data_tensor,
         distorted_image_tensor) = add_input_distortions(
            flip_left_right, random_crop, random_scale,
            random_brightness, model_info['input_width'],
            model_info['input_height'], model_info['input_depth'],
            model_info['input_mean'], model_info['input_std'])
    else:
        # We'll make sure we've calculated the 'bottleneck' image sum
        maries and
        # cached them on disk.
        cache_bottlenecks(sess, image_lists, image_dir,
                           bottleneck_dir, jpeg_data_tensor,
                           decoded_image_tensor, resized_image_tensor,
                           bottleneck_tensor, architecture)

    # Add the new layer that we'll be training.
    (train_step, cross_entropy, bottleneck_input, ground_truth_inpu
    t,
     final_tensor) = add_final_training_ops(
        len(image_lists.keys()), final_tensor_name, bottleneck_ten
        sor,
        model_info['bottleneck_tensor_size'])

    # Create the operations we need to evaluate the accuracy of our
    new layer.
    evaluation_step, prediction = add_evaluation_step(
        final_tensor, ground_truth_input)

    # Merge all the summaries and write them out to the summaries_dir
    merged = tf.summary.merge_all()
    train_writer = tf.summary.FileWriter(summaries_dir + '/train',
        sess.graph)

    validation_writer = tf.summary.FileWriter(summaries_dir + '/val
    idation')

    # Set up all our weights to their initial default values.
    init = tf.global_variables_initializer()
    sess.run(init)

    # Run the training for as many cycles as requested on the comma
    nd line.

```

```

    for i in range(how_many_training_steps):
        # Get a batch of input bottleneck values, either calculated f
resh every
        # time with distortions applied, or from the cache stored on
disk.
        if do_distort_images:
            (train_bottlenecks,
             train_ground_truth) = get_random_distorted_bottlenecks(
                sess, image_lists, train_batch_size, 'training',
                image_dir, distorted_jpeg_data_tensor,
                distorted_image_tensor, resized_image_tensor, bottlene
ck_tensor)
        else:
            (train_bottlenecks,
             train_ground_truth, _) = get_random_cached_bottlenecks(
                sess, image_lists, train_batch_size, 'training',
                bottleneck_dir, image_dir, jpeg_data_tensor,
                decoded_image_tensor, resized_image_tensor, bottleneck
_tensor,
                architecture)

        # Feed the bottlenecks and ground truth into the graph, and r
un a training
        # step. Capture training summaries for TensorBoard with the `
merged` op.
        train_summary, _ = sess.run(
            [merged, train_step],
            feed_dict={bottleneck_input: train_bottlenecks,
                       ground_truth_input: train_ground_truth})
        train_writer.add_summary(train_summary, i)

        # Every so often, print out how well the graph is training.
        is_last_step = (i + 1 == how_many_training_steps)
        if (i % eval_step_interval) == 0 or is_last_step:
            train_accuracy, cross_entropy_value = sess.run(
                [evaluation_step, cross_entropy],
                feed_dict={bottleneck_input: train_bottlenecks,
                           ground_truth_input: train_ground_truth})
            tf.logging.info('%s: Step %d: Train accuracy = %.1f%%' %
                            (datetime.now(), i, train_accuracy * 100))
            tf.logging.info('%s: Step %d: Cross entropy = %f' %
                            (datetime.now(), i, cross_entropy_value))
            validation_bottlenecks, validation_ground_truth, _ = (
                get_random_cached_bottlenecks(
                    sess, image_lists, validation_batch_size, 'validati
on',
                    bottleneck_dir, image_dir, jpeg_data_tensor,
                    decoded_image_tensor, resized_image_tensor, bottlen
eck_tensor,
                    architecture))

            # Run a validation step and capture training summaries for
TensorBoard
            # with the `merged` op.
            validation_summary, validation_accuracy = sess.run(
                [merged, evaluation_step],
                feed_dict={bottleneck_input: validation_bottlenecks,
                           ground_truth_input: validation_ground_truth})

```

```

)
    validation_writer.add_summary(validation_summary, i)
    tf.logging.info('%s: Step %d: Validation accuracy = %.1f%%
(N=%d)' %
                    (datetime.now(), i, validation_accuracy * 1
00,
                     len(validation_bottlenecks)))

    # Store intermediate results
    intermediate_frequency = intermediate_store_frequency

    if (intermediate_frequency > 0 and (i % intermediate_frequenc
y == 0)
        and i > 0):
        intermediate_file_name = (intermediate_output_graphs_dir +
                                'intermediate_' + str(i) + '.pb')
        tf.logging.info('Save intermediate result to : ' +
                        intermediate_file_name)
        save_graph_to_file(sess, graph, intermediate_file_name)

    # We've completed all our training, so run a final test evaluat
ion on
some new images we haven't used before.
    test_bottlenecks, test_ground_truth, test_filenames = (
        get_random_cached_bottlenecks(
            sess, image_lists, test_batch_size, 'testing',
            bottleneck_dir, image_dir, jpeg_data_tensor,
            decoded_image_tensor, resized_image_tensor, bottleneck_
tensor,
            architecture))
    test_accuracy, predictions = sess.run(
        [evaluation_step, prediction],
        feed_dict={bottleneck_input: test_bottlenecks,
                    ground_truth_input: test_ground_truth})
    tf.logging.info('Final test accuracy = %.1f%% (N=%d)' %
                    (test_accuracy * 100, len(test_bottlenecks)))

    if print_misclassified_test_images:
        tf.logging.info('=== MISCLASSIFIED TEST IMAGES ===')
        for i, test_filename in enumerate(test_filenames):
            if predictions[i] != test_ground_truth[i].argmax():
                tf.logging.info('%70s  %s' %
                                (test_filename,
                                 list(image_lists.keys())[predictions[i]]
))

    # Write out the trained graph and labels with the weights store
d as
constants.
    save_graph_to_file(sess, graph, output_graph)
    with gfile.FastGFile(output_labels, 'w') as f:
        f.write('\n'.join(image_lists.keys()) + '\n')

```

```

INFO:tensorflow:100 bottleneck files created.
INFO:tensorflow:200 bottleneck files created.
INFO:tensorflow:300 bottleneck files created.
INFO:tensorflow:400 bottleneck files created.

```

[illegible]

[illegible]

```
INFO:tensorflow:11900 bottleneck files created.
INFO:tensorflow:12000 bottleneck files created.
INFO:tensorflow:12100 bottleneck files created.
INFO:tensorflow:12200 bottleneck files created.
INFO:tensorflow:12300 bottleneck files created.
INFO:tensorflow:12400 bottleneck files created.
INFO:tensorflow:12500 bottleneck files created.
INFO:tensorflow:12600 bottleneck files created.
INFO:tensorflow:12700 bottleneck files created.
WARNING:tensorflow:From /anaconda3/lib/python3.6/site-packages/tensorflow/python/framework/op_def_library.py:263: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From <ipython-input-18-06d43fde6b60>:56: softmax_cross_entropy_with_logits (from tensorflow.python.ops.nn_ops) is deprecated and will be removed in a future version.
Instructions for updating:
```

Future major versions of TensorFlow will allow gradients to flow into the labels input on backprop by default.

See ``tf.nn.softmax_cross_entropy_with_logits_v2``.

```
INFO:tensorflow:2019-04-19 16:22:34.621011: Step 0: Train accuracy = 13.0%
INFO:tensorflow:2019-04-19 16:22:34.622101: Step 0: Cross entropy = 3.061954
INFO:tensorflow:2019-04-19 16:22:35.042847: Step 0: Validation accuracy = 14.0% (N=100)
INFO:tensorflow:2019-04-19 16:22:35.793847: Step 10: Train accuracy = 33.0%
INFO:tensorflow:2019-04-19 16:22:35.794574: Step 10: Cross entropy = 5.970832
INFO:tensorflow:2019-04-19 16:22:35.866127: Step 10: Validation accuracy = 26.0% (N=100)
INFO:tensorflow:2019-04-19 16:22:36.608350: Step 20: Train accuracy = 47.0%
INFO:tensorflow:2019-04-19 16:22:36.609042: Step 20: Cross entropy = 2.818956
INFO:tensorflow:2019-04-19 16:22:36.682358: Step 20: Validation accuracy = 42.0% (N=100)
INFO:tensorflow:2019-04-19 16:22:37.397043: Step 30: Train accuracy = 49.0%
INFO:tensorflow:2019-04-19 16:22:37.397732: Step 30: Cross entropy = 2.694890
INFO:tensorflow:2019-04-19 16:22:37.470440: Step 30: Validation accuracy = 32.0% (N=100)
INFO:tensorflow:2019-04-19 16:22:38.216148: Step 40: Train accuracy = 47.0%
INFO:tensorflow:2019-04-19 16:22:38.217453: Step 40: Cross entropy = 1.861224
INFO:tensorflow:2019-04-19 16:22:38.331172: Step 40: Validation accuracy = 43.0% (N=100)
INFO:tensorflow:2019-04-19 16:22:39.092034: Step 50: Train accuracy = 47.0%
```



INFO:tensorflow:2019-04-19 16:22:39.092847: Step 50: Cross entropy = 2.080700  
INFO:tensorflow:2019-04-19 16:22:39.169914: Step 50: Validation accuracy = 36.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:39.911146: Step 60: Train accuracy = 63.0%  
INFO:tensorflow:2019-04-19 16:22:39.911856: Step 60: Cross entropy = 1.402826  
INFO:tensorflow:2019-04-19 16:22:39.992399: Step 60: Validation accuracy = 51.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:40.704541: Step 70: Train accuracy = 49.0%  
INFO:tensorflow:2019-04-19 16:22:40.705791: Step 70: Cross entropy = 2.175385  
INFO:tensorflow:2019-04-19 16:22:40.775881: Step 70: Validation accuracy = 43.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:41.490153: Step 80: Train accuracy = 58.0%  
INFO:tensorflow:2019-04-19 16:22:41.490872: Step 80: Cross entropy = 1.719470  
INFO:tensorflow:2019-04-19 16:22:41.560025: Step 80: Validation accuracy = 48.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:42.287766: Step 90: Train accuracy = 51.0%  
INFO:tensorflow:2019-04-19 16:22:42.288470: Step 90: Cross entropy = 1.705877  
INFO:tensorflow:2019-04-19 16:22:42.368376: Step 90: Validation accuracy = 43.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:43.102003: Step 100: Train accuracy = 65.0%  
INFO:tensorflow:2019-04-19 16:22:43.102722: Step 100: Cross entropy = 1.176083  
INFO:tensorflow:2019-04-19 16:22:43.171548: Step 100: Validation accuracy = 54.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:43.817913: Step 110: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:22:43.818642: Step 110: Cross entropy = 1.078799  
INFO:tensorflow:2019-04-19 16:22:43.888779: Step 110: Validation accuracy = 48.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:44.540810: Step 120: Train accuracy = 63.0%  
INFO:tensorflow:2019-04-19 16:22:44.541730: Step 120: Cross entropy = 1.124328  
INFO:tensorflow:2019-04-19 16:22:44.620807: Step 120: Validation accuracy = 60.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:45.333577: Step 130: Train accuracy = 61.0%  
INFO:tensorflow:2019-04-19 16:22:45.334273: Step 130: Cross entropy = 1.288900  
INFO:tensorflow:2019-04-19 16:22:45.399620: Step 130: Validation accuracy = 53.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:46.066121: Step 140: Train accuracy = 71.0%  
INFO:tensorflow:2019-04-19 16:22:46.066818: Step 140: Cross entropy = 0.845092  
INFO:tensorflow:2019-04-19 16:22:46.140289: Step 140: Validation a

ccuracy = 64.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:46.810528: Step 150: Train accuracy = 69.0%  
INFO:tensorflow:2019-04-19 16:22:46.811406: Step 150: Cross entropy = 1.379404  
INFO:tensorflow:2019-04-19 16:22:46.875973: Step 150: Validation accuracy = 61.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:47.516614: Step 160: Train accuracy = 64.0%  
INFO:tensorflow:2019-04-19 16:22:47.517501: Step 160: Cross entropy = 0.988481  
INFO:tensorflow:2019-04-19 16:22:47.585937: Step 160: Validation accuracy = 58.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:48.270022: Step 170: Train accuracy = 69.0%  
INFO:tensorflow:2019-04-19 16:22:48.270817: Step 170: Cross entropy = 1.490823  
INFO:tensorflow:2019-04-19 16:22:48.337132: Step 170: Validation accuracy = 61.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:49.006550: Step 180: Train accuracy = 63.0%  
INFO:tensorflow:2019-04-19 16:22:49.007254: Step 180: Cross entropy = 1.167296  
INFO:tensorflow:2019-04-19 16:22:49.079963: Step 180: Validation accuracy = 55.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:49.758225: Step 190: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:22:49.759275: Step 190: Cross entropy = 0.748049  
INFO:tensorflow:2019-04-19 16:22:49.824492: Step 190: Validation accuracy = 72.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:50.500612: Step 200: Train accuracy = 74.0%  
INFO:tensorflow:2019-04-19 16:22:50.501382: Step 200: Cross entropy = 0.937247  
INFO:tensorflow:2019-04-19 16:22:50.573595: Step 200: Validation accuracy = 63.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:51.250296: Step 210: Train accuracy = 73.0%  
INFO:tensorflow:2019-04-19 16:22:51.250987: Step 210: Cross entropy = 0.956763  
INFO:tensorflow:2019-04-19 16:22:51.319636: Step 210: Validation accuracy = 60.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:51.994690: Step 220: Train accuracy = 67.0%  
INFO:tensorflow:2019-04-19 16:22:51.995391: Step 220: Cross entropy = 1.060545  
INFO:tensorflow:2019-04-19 16:22:52.061403: Step 220: Validation accuracy = 61.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:52.710160: Step 230: Train accuracy = 67.0%  
INFO:tensorflow:2019-04-19 16:22:52.710877: Step 230: Cross entropy = 0.962022  
INFO:tensorflow:2019-04-19 16:22:52.778727: Step 230: Validation accuracy = 58.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:53.424280: Step 240: Train accuracy = 70.0%

INFO:tensorflow:2019-04-19 16:22:53.424947: Step 240: Cross entropy = 1.020624  
INFO:tensorflow:2019-04-19 16:22:53.493984: Step 240: Validation accuracy = 62.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:54.114153: Step 250: Train accuracy = 71.0%  
INFO:tensorflow:2019-04-19 16:22:54.114864: Step 250: Cross entropy = 1.046482  
INFO:tensorflow:2019-04-19 16:22:54.182880: Step 250: Validation accuracy = 60.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:54.836279: Step 260: Train accuracy = 72.0%  
INFO:tensorflow:2019-04-19 16:22:54.836967: Step 260: Cross entropy = 1.159551  
INFO:tensorflow:2019-04-19 16:22:54.908544: Step 260: Validation accuracy = 61.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:55.537605: Step 270: Train accuracy = 70.0%  
INFO:tensorflow:2019-04-19 16:22:55.538301: Step 270: Cross entropy = 0.994852  
INFO:tensorflow:2019-04-19 16:22:55.605295: Step 270: Validation accuracy = 72.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:56.244780: Step 280: Train accuracy = 68.0%  
INFO:tensorflow:2019-04-19 16:22:56.245588: Step 280: Cross entropy = 0.785224  
INFO:tensorflow:2019-04-19 16:22:56.307007: Step 280: Validation accuracy = 48.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:56.963394: Step 290: Train accuracy = 72.0%  
INFO:tensorflow:2019-04-19 16:22:56.964116: Step 290: Cross entropy = 0.837372  
INFO:tensorflow:2019-04-19 16:22:57.030457: Step 290: Validation accuracy = 59.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:57.699055: Step 300: Train accuracy = 78.0%  
INFO:tensorflow:2019-04-19 16:22:57.699729: Step 300: Cross entropy = 0.653664  
INFO:tensorflow:2019-04-19 16:22:57.771122: Step 300: Validation accuracy = 66.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:58.404866: Step 310: Train accuracy = 74.0%  
INFO:tensorflow:2019-04-19 16:22:58.405585: Step 310: Cross entropy = 0.891529  
INFO:tensorflow:2019-04-19 16:22:58.484672: Step 310: Validation accuracy = 62.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:59.140213: Step 320: Train accuracy = 67.0%  
INFO:tensorflow:2019-04-19 16:22:59.140898: Step 320: Cross entropy = 1.207222  
INFO:tensorflow:2019-04-19 16:22:59.206804: Step 320: Validation accuracy = 66.0% (N=100)  
INFO:tensorflow:2019-04-19 16:22:59.830683: Step 330: Train accuracy = 75.0%  
INFO:tensorflow:2019-04-19 16:22:59.831528: Step 330: Cross entropy = 0.942613  
INFO:tensorflow:2019-04-19 16:22:59.892697: Step 330: Validation a

ccuracy = 54.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:00.501672: Step 340: Train accuracy = 71.0%  
INFO:tensorflow:2019-04-19 16:23:00.502428: Step 340: Cross entropy = 1.114180  
INFO:tensorflow:2019-04-19 16:23:00.566323: Step 340: Validation accuracy = 64.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:01.168111: Step 350: Train accuracy = 73.0%  
INFO:tensorflow:2019-04-19 16:23:01.168812: Step 350: Cross entropy = 0.943369  
INFO:tensorflow:2019-04-19 16:23:01.231134: Step 350: Validation accuracy = 72.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:01.825483: Step 360: Train accuracy = 78.0%  
INFO:tensorflow:2019-04-19 16:23:01.826369: Step 360: Cross entropy = 0.686456  
INFO:tensorflow:2019-04-19 16:23:01.890009: Step 360: Validation accuracy = 70.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:02.486034: Step 370: Train accuracy = 65.0%  
INFO:tensorflow:2019-04-19 16:23:02.486742: Step 370: Cross entropy = 1.698057  
INFO:tensorflow:2019-04-19 16:23:02.550818: Step 370: Validation accuracy = 58.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:03.128962: Step 380: Train accuracy = 71.0%  
INFO:tensorflow:2019-04-19 16:23:03.129665: Step 380: Cross entropy = 0.992413  
INFO:tensorflow:2019-04-19 16:23:03.189417: Step 380: Validation accuracy = 70.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:03.766007: Step 390: Train accuracy = 84.0%  
INFO:tensorflow:2019-04-19 16:23:03.766796: Step 390: Cross entropy = 0.670173  
INFO:tensorflow:2019-04-19 16:23:03.826535: Step 390: Validation accuracy = 65.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:04.394713: Step 400: Train accuracy = 70.0%  
INFO:tensorflow:2019-04-19 16:23:04.395582: Step 400: Cross entropy = 0.997186  
INFO:tensorflow:2019-04-19 16:23:04.458617: Step 400: Validation accuracy = 57.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:05.037170: Step 410: Train accuracy = 86.0%  
INFO:tensorflow:2019-04-19 16:23:05.037892: Step 410: Cross entropy = 0.494253  
INFO:tensorflow:2019-04-19 16:23:05.099990: Step 410: Validation accuracy = 66.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:05.655968: Step 420: Train accuracy = 71.0%  
INFO:tensorflow:2019-04-19 16:23:05.656985: Step 420: Cross entropy = 1.435556  
INFO:tensorflow:2019-04-19 16:23:05.715607: Step 420: Validation accuracy = 66.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:06.269585: Step 430: Train accuracy = 64.0%

INFO:tensorflow:2019-04-19 16:23:06.270314: Step 430: Cross entropy = 0.933639  
INFO:tensorflow:2019-04-19 16:23:06.329115: Step 430: Validation accuracy = 63.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:06.888705: Step 440: Train accuracy = 78.0%  
INFO:tensorflow:2019-04-19 16:23:06.889522: Step 440: Cross entropy = 1.054687  
INFO:tensorflow:2019-04-19 16:23:06.951761: Step 440: Validation accuracy = 64.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:07.496110: Step 450: Train accuracy = 78.0%  
INFO:tensorflow:2019-04-19 16:23:07.496914: Step 450: Cross entropy = 1.018594  
INFO:tensorflow:2019-04-19 16:23:07.549541: Step 450: Validation accuracy = 65.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:08.104181: Step 460: Train accuracy = 68.0%  
INFO:tensorflow:2019-04-19 16:23:08.104821: Step 460: Cross entropy = 1.577670  
INFO:tensorflow:2019-04-19 16:23:08.167025: Step 460: Validation accuracy = 61.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:08.766593: Step 470: Train accuracy = 71.0%  
INFO:tensorflow:2019-04-19 16:23:08.767334: Step 470: Cross entropy = 1.936523  
INFO:tensorflow:2019-04-19 16:23:08.826052: Step 470: Validation accuracy = 61.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:09.359435: Step 480: Train accuracy = 75.0%  
INFO:tensorflow:2019-04-19 16:23:09.360134: Step 480: Cross entropy = 0.681986  
INFO:tensorflow:2019-04-19 16:23:09.414236: Step 480: Validation accuracy = 70.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:09.956726: Step 490: Train accuracy = 71.0%  
INFO:tensorflow:2019-04-19 16:23:09.957829: Step 490: Cross entropy = 1.089501  
INFO:tensorflow:2019-04-19 16:23:10.015367: Step 490: Validation accuracy = 69.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:10.564535: Step 500: Train accuracy = 74.0%  
INFO:tensorflow:2019-04-19 16:23:10.565438: Step 500: Cross entropy = 0.845896  
INFO:tensorflow:2019-04-19 16:23:10.630128: Step 500: Validation accuracy = 63.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:11.177526: Step 510: Train accuracy = 64.0%  
INFO:tensorflow:2019-04-19 16:23:11.178254: Step 510: Cross entropy = 1.158226  
INFO:tensorflow:2019-04-19 16:23:11.238216: Step 510: Validation accuracy = 55.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:11.799027: Step 520: Train accuracy = 76.0%  
INFO:tensorflow:2019-04-19 16:23:11.799764: Step 520: Cross entropy = 0.994964  
INFO:tensorflow:2019-04-19 16:23:11.869502: Step 520: Validation a

ccuracy = 55.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:12.444082: Step 530: Train accuracy = 67.0%  
INFO:tensorflow:2019-04-19 16:23:12.444836: Step 530: Cross entropy = 0.788251  
INFO:tensorflow:2019-04-19 16:23:12.509681: Step 530: Validation accuracy = 68.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:13.105740: Step 540: Train accuracy = 84.0%  
INFO:tensorflow:2019-04-19 16:23:13.106507: Step 540: Cross entropy = 0.357493  
INFO:tensorflow:2019-04-19 16:23:13.166747: Step 540: Validation accuracy = 76.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:13.816167: Step 550: Train accuracy = 83.0%  
INFO:tensorflow:2019-04-19 16:23:13.816968: Step 550: Cross entropy = 0.541631  
INFO:tensorflow:2019-04-19 16:23:13.886190: Step 550: Validation accuracy = 65.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:14.451239: Step 560: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:23:14.451964: Step 560: Cross entropy = 0.639227  
INFO:tensorflow:2019-04-19 16:23:14.507766: Step 560: Validation accuracy = 68.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:15.082511: Step 570: Train accuracy = 70.0%  
INFO:tensorflow:2019-04-19 16:23:15.083256: Step 570: Cross entropy = 0.806414  
INFO:tensorflow:2019-04-19 16:23:15.148618: Step 570: Validation accuracy = 66.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:15.763760: Step 580: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:23:15.764468: Step 580: Cross entropy = 0.723219  
INFO:tensorflow:2019-04-19 16:23:15.828468: Step 580: Validation accuracy = 58.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:16.429737: Step 590: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:23:16.430494: Step 590: Cross entropy = 0.669706  
INFO:tensorflow:2019-04-19 16:23:16.494066: Step 590: Validation accuracy = 71.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:17.155851: Step 600: Train accuracy = 64.0%  
INFO:tensorflow:2019-04-19 16:23:17.156763: Step 600: Cross entropy = 1.023656  
INFO:tensorflow:2019-04-19 16:23:17.224602: Step 600: Validation accuracy = 58.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:17.858732: Step 610: Train accuracy = 75.0%  
INFO:tensorflow:2019-04-19 16:23:17.859717: Step 610: Cross entropy = 0.744248  
INFO:tensorflow:2019-04-19 16:23:17.933926: Step 610: Validation accuracy = 66.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:18.583887: Step 620: Train accuracy = 74.0%

INFO:tensorflow:2019-04-19 16:23:18.584582: Step 620: Cross entropy = 0.942072  
INFO:tensorflow:2019-04-19 16:23:18.646154: Step 620: Validation accuracy = 66.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:19.273459: Step 630: Train accuracy = 80.0%  
INFO:tensorflow:2019-04-19 16:23:19.274182: Step 630: Cross entropy = 0.640617  
INFO:tensorflow:2019-04-19 16:23:19.333281: Step 630: Validation accuracy = 74.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:19.947050: Step 640: Train accuracy = 75.0%  
INFO:tensorflow:2019-04-19 16:23:19.947747: Step 640: Cross entropy = 0.990996  
INFO:tensorflow:2019-04-19 16:23:20.015726: Step 640: Validation accuracy = 60.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:20.632183: Step 650: Train accuracy = 72.0%  
INFO:tensorflow:2019-04-19 16:23:20.632878: Step 650: Cross entropy = 1.168968  
INFO:tensorflow:2019-04-19 16:23:20.689326: Step 650: Validation accuracy = 68.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:21.281094: Step 660: Train accuracy = 76.0%  
INFO:tensorflow:2019-04-19 16:23:21.281782: Step 660: Cross entropy = 0.773897  
INFO:tensorflow:2019-04-19 16:23:21.339984: Step 660: Validation accuracy = 77.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:21.926816: Step 670: Train accuracy = 75.0%  
INFO:tensorflow:2019-04-19 16:23:21.927528: Step 670: Cross entropy = 0.680679  
INFO:tensorflow:2019-04-19 16:23:21.992113: Step 670: Validation accuracy = 74.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:22.585953: Step 680: Train accuracy = 79.0%  
INFO:tensorflow:2019-04-19 16:23:22.586644: Step 680: Cross entropy = 0.738183  
INFO:tensorflow:2019-04-19 16:23:22.661842: Step 680: Validation accuracy = 71.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:23.276436: Step 690: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:23:23.277224: Step 690: Cross entropy = 0.727368  
INFO:tensorflow:2019-04-19 16:23:23.339538: Step 690: Validation accuracy = 76.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:23.979166: Step 700: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:23:23.979969: Step 700: Cross entropy = 0.759917  
INFO:tensorflow:2019-04-19 16:23:24.049450: Step 700: Validation accuracy = 71.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:24.700168: Step 710: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:23:24.700859: Step 710: Cross entropy = 0.833123  
INFO:tensorflow:2019-04-19 16:23:24.771051: Step 710: Validation a

ccuracy = 66.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:25.402086: Step 720: Train accuracy = 79.0%  
INFO:tensorflow:2019-04-19 16:23:25.402760: Step 720: Cross entropy = 0.910988  
INFO:tensorflow:2019-04-19 16:23:25.466920: Step 720: Validation accuracy = 72.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:26.120265: Step 730: Train accuracy = 74.0%  
INFO:tensorflow:2019-04-19 16:23:26.120934: Step 730: Cross entropy = 0.803555  
INFO:tensorflow:2019-04-19 16:23:26.187276: Step 730: Validation accuracy = 68.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:26.839986: Step 740: Train accuracy = 75.0%  
INFO:tensorflow:2019-04-19 16:23:26.840696: Step 740: Cross entropy = 1.122094  
INFO:tensorflow:2019-04-19 16:23:26.910158: Step 740: Validation accuracy = 65.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:27.558743: Step 750: Train accuracy = 83.0%  
INFO:tensorflow:2019-04-19 16:23:27.560535: Step 750: Cross entropy = 0.737640  
INFO:tensorflow:2019-04-19 16:23:27.632186: Step 750: Validation accuracy = 69.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:28.261408: Step 760: Train accuracy = 80.0%  
INFO:tensorflow:2019-04-19 16:23:28.262120: Step 760: Cross entropy = 0.706354  
INFO:tensorflow:2019-04-19 16:23:28.336478: Step 760: Validation accuracy = 66.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:29.017443: Step 770: Train accuracy = 79.0%  
INFO:tensorflow:2019-04-19 16:23:29.018174: Step 770: Cross entropy = 0.500313  
INFO:tensorflow:2019-04-19 16:23:29.083264: Step 770: Validation accuracy = 67.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:29.741646: Step 780: Train accuracy = 76.0%  
INFO:tensorflow:2019-04-19 16:23:29.742365: Step 780: Cross entropy = 0.924634  
INFO:tensorflow:2019-04-19 16:23:29.807875: Step 780: Validation accuracy = 65.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:30.464603: Step 790: Train accuracy = 68.0%  
INFO:tensorflow:2019-04-19 16:23:30.465335: Step 790: Cross entropy = 0.981651  
INFO:tensorflow:2019-04-19 16:23:30.534354: Step 790: Validation accuracy = 62.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:31.208256: Step 800: Train accuracy = 68.0%  
INFO:tensorflow:2019-04-19 16:23:31.208944: Step 800: Cross entropy = 1.254277  
INFO:tensorflow:2019-04-19 16:23:31.277988: Step 800: Validation accuracy = 51.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:31.929800: Step 810: Train accuracy = 70.0%



INFO:tensorflow:2019-04-19 16:23:31.930505: Step 810: Cross entropy = 0.758481  
INFO:tensorflow:2019-04-19 16:23:32.000630: Step 810: Validation accuracy = 72.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:32.647575: Step 820: Train accuracy = 79.0%  
INFO:tensorflow:2019-04-19 16:23:32.648251: Step 820: Cross entropy = 0.721066  
INFO:tensorflow:2019-04-19 16:23:32.719359: Step 820: Validation accuracy = 68.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:33.392154: Step 830: Train accuracy = 75.0%  
INFO:tensorflow:2019-04-19 16:23:33.392996: Step 830: Cross entropy = 0.832695  
INFO:tensorflow:2019-04-19 16:23:33.476192: Step 830: Validation accuracy = 64.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:34.157655: Step 840: Train accuracy = 85.0%  
INFO:tensorflow:2019-04-19 16:23:34.158421: Step 840: Cross entropy = 0.595535  
INFO:tensorflow:2019-04-19 16:23:34.234679: Step 840: Validation accuracy = 67.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:34.856031: Step 850: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:23:34.856926: Step 850: Cross entropy = 0.993486  
INFO:tensorflow:2019-04-19 16:23:34.924331: Step 850: Validation accuracy = 63.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:35.604663: Step 860: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:23:35.605351: Step 860: Cross entropy = 0.818102  
INFO:tensorflow:2019-04-19 16:23:35.680052: Step 860: Validation accuracy = 75.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:36.347821: Step 870: Train accuracy = 74.0%  
INFO:tensorflow:2019-04-19 16:23:36.348774: Step 870: Cross entropy = 1.220001  
INFO:tensorflow:2019-04-19 16:23:36.415417: Step 870: Validation accuracy = 71.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:37.080998: Step 880: Train accuracy = 69.0%  
INFO:tensorflow:2019-04-19 16:23:37.081694: Step 880: Cross entropy = 0.883006  
INFO:tensorflow:2019-04-19 16:23:37.156941: Step 880: Validation accuracy = 71.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:37.805704: Step 890: Train accuracy = 82.0%  
INFO:tensorflow:2019-04-19 16:23:37.806400: Step 890: Cross entropy = 0.709523  
INFO:tensorflow:2019-04-19 16:23:37.870440: Step 890: Validation accuracy = 69.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:38.543251: Step 900: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:23:38.543949: Step 900: Cross entropy = 1.080867  
INFO:tensorflow:2019-04-19 16:23:38.617923: Step 900: Validation a

ccuracy = 68.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:39.296248: Step 910: Train accuracy = 64.0%  
INFO:tensorflow:2019-04-19 16:23:39.297283: Step 910: Cross entropy = 1.254931  
INFO:tensorflow:2019-04-19 16:23:39.365501: Step 910: Validation accuracy = 59.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:40.038755: Step 920: Train accuracy = 72.0%  
INFO:tensorflow:2019-04-19 16:23:40.039442: Step 920: Cross entropy = 0.893486  
INFO:tensorflow:2019-04-19 16:23:40.104628: Step 920: Validation accuracy = 74.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:40.723413: Step 930: Train accuracy = 81.0%  
INFO:tensorflow:2019-04-19 16:23:40.724099: Step 930: Cross entropy = 0.609884  
INFO:tensorflow:2019-04-19 16:23:40.795786: Step 930: Validation accuracy = 76.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:41.425433: Step 940: Train accuracy = 77.0%  
INFO:tensorflow:2019-04-19 16:23:41.426208: Step 940: Cross entropy = 0.643411  
INFO:tensorflow:2019-04-19 16:23:41.494840: Step 940: Validation accuracy = 75.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:42.154237: Step 950: Train accuracy = 81.0%  
INFO:tensorflow:2019-04-19 16:23:42.155308: Step 950: Cross entropy = 0.532883  
INFO:tensorflow:2019-04-19 16:23:42.219952: Step 950: Validation accuracy = 68.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:42.829749: Step 960: Train accuracy = 80.0%  
INFO:tensorflow:2019-04-19 16:23:42.830448: Step 960: Cross entropy = 0.573259  
INFO:tensorflow:2019-04-19 16:23:42.896827: Step 960: Validation accuracy = 62.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:43.533685: Step 970: Train accuracy = 81.0%  
INFO:tensorflow:2019-04-19 16:23:43.534363: Step 970: Cross entropy = 0.607507  
INFO:tensorflow:2019-04-19 16:23:43.599430: Step 970: Validation accuracy = 63.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:44.227920: Step 980: Train accuracy = 76.0%  
INFO:tensorflow:2019-04-19 16:23:44.229031: Step 980: Cross entropy = 0.717568  
INFO:tensorflow:2019-04-19 16:23:44.295992: Step 980: Validation accuracy = 65.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:44.905825: Step 990: Train accuracy = 86.0%  
INFO:tensorflow:2019-04-19 16:23:44.906535: Step 990: Cross entropy = 0.538438  
INFO:tensorflow:2019-04-19 16:23:44.970004: Step 990: Validation accuracy = 69.0% (N=100)  
INFO:tensorflow:2019-04-19 16:23:45.529867: Step 999: Train accuracy = 81.0%

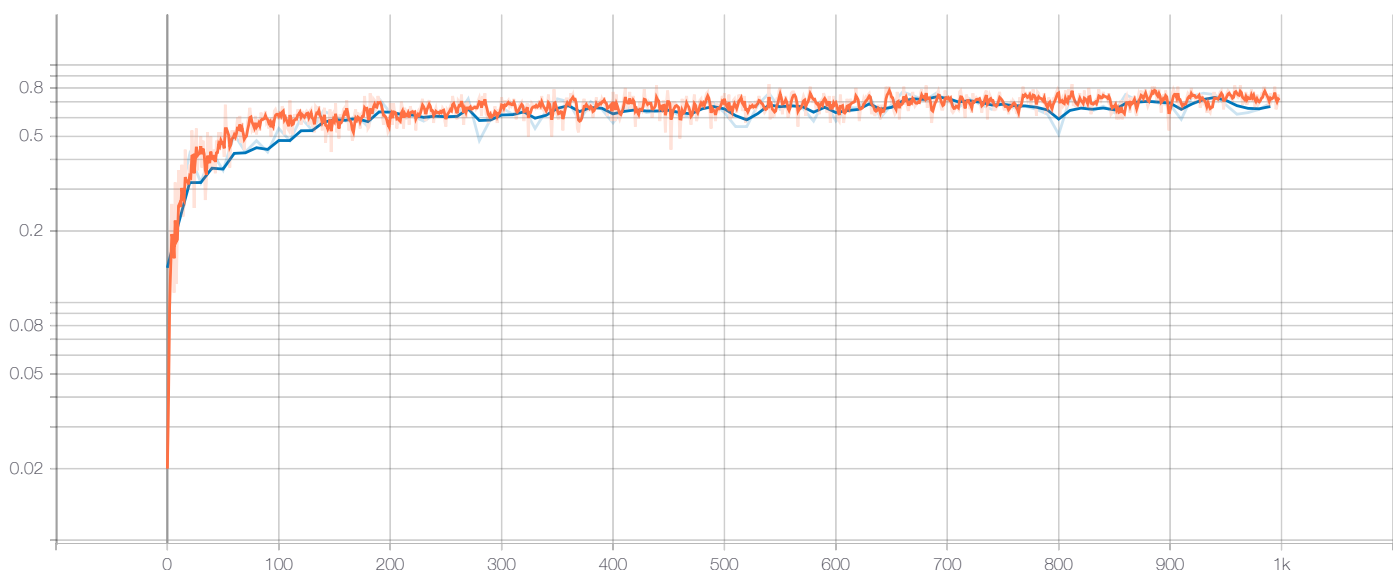
```
INFO:tensorflow:2019-04-19 16:23:45.530610: Step 999: Cross entropy = 0.593006
INFO:tensorflow:2019-04-19 16:23:45.594530: Step 999: Validation accuracy = 57.0% (N=100)
INFO:tensorflow:Final test accuracy = 68.0% (N=100)
WARNING:tensorflow:From <ipython-input-20-50a32f7ca1b2>:3: convert_variables_to_constants (from tensorflow.python.framework.graph_util_impl) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.compat.v1.graph_util.convert_variables_to_constants
WARNING:tensorflow:From /anaconda3/lib/python3.6/site-packages/tensorflow/python/framework/graph_util_impl.py:245: extract_sub_graph (from tensorflow.python.framework.graph_util_impl) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.compat.v1.graph_util.extract_sub_graph
INFO:tensorflow:Froze 2 variables.
INFO:tensorflow:Converted 2 variables to const ops.
```

## ANALYSE RESULTS

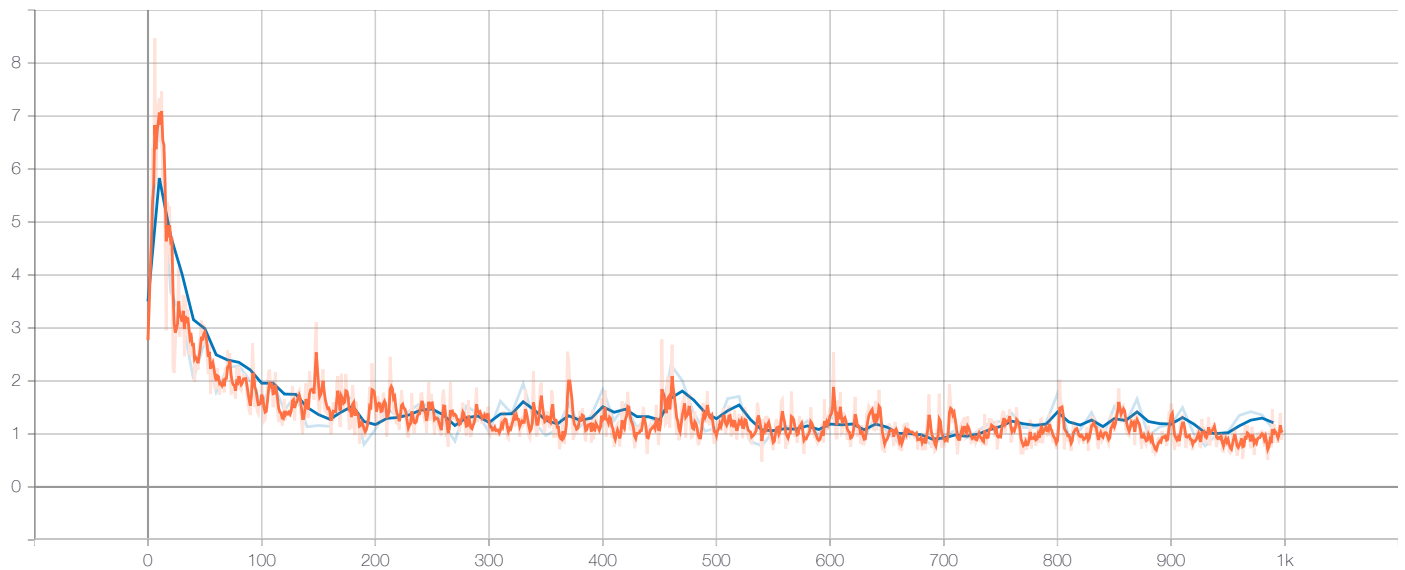
As it trains, you'll see a series of step outputs, each one showing training accuracy, validation accuracy, and the cross entropy:

- The training accuracy shows the percentage of the images used in the current training batch that were labeled with the correct class.
- The validation accuracy is the precision (percentage of correctly-labelled images) on a randomly-selected group of images from a different set.
- Cross entropy is a loss function that gives a glimpse into how well the learning process is progressing. (Lower numbers are better.)

## TRAINING ACCURACY : 81%



## CROSS ENTROPY: LOWER NUMBERS ARE BETTER!



Two lines are shown. The orange line shows the accuracy of the model on the training data. While the blue line shows the accuracy on the test set (which was not used for training). This is a much better measure of the true performance of the network. If the training accuracy continues to rise while the validation accuracy decreases then the model is said to be "overfitting". Overfitting is when the model begins to memorize the training set instead of understanding general patterns in the data.

As the process continues, you should see the reported accuracy improve. After all the training steps are complete, the script runs a final test accuracy evaluation on a set of images that are kept separate from the training and validation pictures. This test evaluation provides the best estimate of how the trained model will perform on the classification task.

You should see an accuracy value of between 85% and 99%, though the exact value will vary from run to run since there's randomness in the training process. (If you are only training on two classes, you should expect higher accuracy.) This number value indicates the percentage of the images in the test set that are given the correct label after the model is fully trained.

```
In [31]: import tensorflow as tf

img = tf.placeholder(name="img", dtype=tf.float32, shape=(1, 224, 224, 3))
val = img + tf.constant([1., 2., 3.]) + tf.constant([1., 4., 4.])
out = tf.identity(val, name="out")
with tf.Session() as sess:
    tflite_model = tf.contrib.lite.toco_convert(sess.graph_def, [img], [out])
    open("fashion.tflite", "wb").write(tflite_model)
```

WARNING: The TensorFlow contrib module will not be included in TensorFlow 2.0.

For more information, please see:

- \* <https://github.com/tensorflow/community/blob/master/rfcs/20180907-contrib-sunset.md>

- \* <https://github.com/tensorflow/addons>

If you depend on functionality not listed there, please file an issue.

WARNING:tensorflow:From <ipython-input-31-f1ea6ee101b7>:7: toco\_convert (from tensorflow.lite.python.convert) is deprecated and will be removed in a future version.

Instructions for updating:

Use `lite.TFLiteConverter` instead.