

Q1

Cutout regularization aims to use both the advantages from dropout as well as the advantages of data augmentation with regards to regularization. It is a regularization technique applied to convolutional neural networks where we remove neighboring parts of input images and also augment the dataset with obstructed versions of existing samples. The idea is to extend the dropout in the sense that we also apply a spatial prior that is relevant for images data as images share local connectivities. The ultimate goal is to force the learning algorithm to get a global sense of the full image rather than learning specific features that might endanger the predictions on unseen data where those features are not present. Finally, the key difference with dropout is that cutout is applied to the input layer so that visual features are removed directly from the image and no dropout is applied in the hidden layer and therefore the image itself is modified which makes cutout similar to dropout. ¶

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In [2]: from __future__ import absolute_import
        from __future__ import division
        from __future__ import print_function
        import tensorflow as tf
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense
        from sklearn.preprocessing import StandardScaler
        from tensorflow.keras.models import Sequential
        from tensorflow.keras import models, layers
        import tensorflow.keras as keras
        from tensorflow.keras.layers import BatchNormalization, LayerNormalizati
on
        import tensorflow as tf
        from tensorflow.keras.layers import Dropout
        import numpy as np
        import matplotlib.pyplot as plt
        if tf.test.gpu_device_name():
            print('Default GPU Device: {}'.format(tf.test.gpu_device_name()))
        else:
            print("Please install GPU version of TF")
        from matplotlib import pyplot
        from tensorflow.keras.datasets import cifar10
        from numpy import save
        from numpy import savetxt
        from numpy import loadtxt
        from time import time
        import pandas as pd

        from tensorflow.keras.layers import Dense, Conv2D
        from tensorflow.keras.layers import BatchNormalization, Activation
        from tensorflow.keras.layers import AveragePooling2D, Input
        from tensorflow.keras.layers import Flatten, add
        from tensorflow.keras.optimizers import Adam
        from tensorflow.keras.callbacks import ModelCheckpoint, LearningRateSche
duler
        from tensorflow.keras.callbacks import ReduceLROnPlateau
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
        from tensorflow.keras.regularizers import l2
        from tensorflow.keras.models import Model
        from tensorflow.keras.datasets import cifar10
        from tensorflow.keras.utils import plot_model
        from tensorflow.keras.utils import to_categorical
        import numpy as np
        import os
        import math
        import numpy as np
        from tensorflow.keras.datasets import cifar10
        import matplotlib.pyplot as plt
        from numpy import savetxt
        from numpy import loadtxt

```

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/Users/taziy/anaconda3/lib/python3.7/site-packages/tensorboard/compat/tensorflow_stub/dtypes.py:541: FutureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
    _np_qint8 = np.dtype [("qint8", np.int8, 1)]
/Users/taziy/anaconda3/lib/python3.7/site-packages/tensorboard/compat/tensorflow_stub/dtypes.py:542: FutureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
    _np_quint8 = np.dtype [("quint8", np.uint8, 1)]
/Users/taziy/anaconda3/lib/python3.7/site-packages/tensorboard/compat/tensorflow_stub/dtypes.py:543: FutureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
    _np_qint16 = np.dtype [("qint16", np.int16, 1)]
/Users/taziy/anaconda3/lib/python3.7/site-packages/tensorboard/compat/tensorflow_stub/dtypes.py:544: FutureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
    _np_quint16 = np.dtype [("quint16", np.uint16, 1)]
/Users/taziy/anaconda3/lib/python3.7/site-packages/tensorboard/compat/tensorflow_stub/dtypes.py:545: FutureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
    _np_qint32 = np.dtype [("qint32", np.int32, 1)]
/Users/taziy/anaconda3/lib/python3.7/site-packages/tensorboard/compat/tensorflow_stub/dtypes.py:550: FutureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
    np_resource = np.dtype [("resource", np.ubyte, 1)]

```

Please install GPU version of TF

```

In [ ]: def apply_mask(image, size=12, n_squares=1):
        h, w, channels = image.shape
        new_image = image
        for _ in range(n_squares):
            y = np.random.randint(h)
            x = np.random.randint(w)
            y1 = np.clip(y - size // 2, 0, h)
            y2 = np.clip(y + size // 2, 0, h)
            x1 = np.clip(x - size // 2, 0, w)
            x2 = np.clip(x + size // 2, 0, w)
            new_image[y1:y2, x1:x2, :] = 0
        return new_image

```

```
In [ ]: (x_train, y_train), (x_test, y_test) = cifar10.load_data()
# Data normalization
m, std = np.mean(x_train), np.std(x_train)
x_train = (x_train - m)/std
x_test = (x_test - m)/std
y_train = tf.keras.utils.to_categorical(y_train)
y_test = tf.keras.utils.to_categorical(y_test)
plt.figure(figsize=(40,20))
print("Original images:")
images_index = [20,100]
for i in range(2):
    tmp = x_train[images_index[i]]
    plt.subplot(330 + 1 + i)
    plt.imshow(tmp)
plt.show()
print("Images with cutout:")
plt.figure(figsize=(40,20))
for i in range(2):
    tmp = x_train[images_index[i]]
    plt.subplot(330 + 1 + i)
    plt.imshow(apply_mask(tmp,size=10))
plt.show()
```

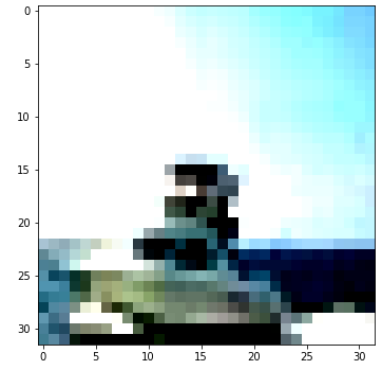
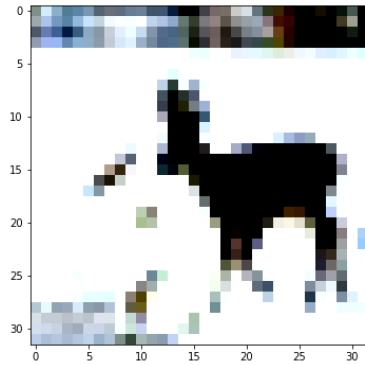
Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>

170500096/170498071 [=====] - 13s 0us/step

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

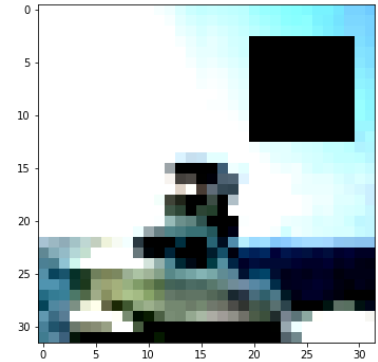
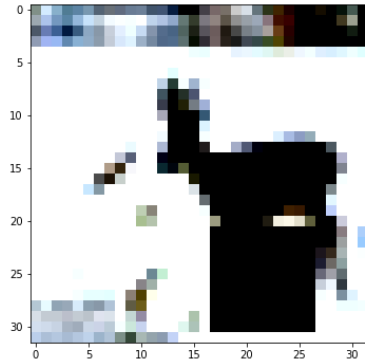
Original images:



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

Images with cutout:



Q2

```

In [ ]: # training parameters
batch_size = 64
epochs = 100
data_augmentation = True
num_classes = 10

# subtracting pixel mean improves accuracy
subtract_pixel_mean = True
n = 7 # so that we use resnet 44 because 6*n+2
depth = n * 6 + 2

# model name, depth and version
model_type = 'ResNet44'

# load the CIFAR10 data.
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# input image dimensions.
input_shape = x_train.shape[1:]

# normalize data.
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255

# if subtract pixel mean is enabled
if subtract_pixel_mean:
    x_train_mean = np.mean(x_train, axis=0)
    x_train -= x_train_mean
    x_test -= x_train_mean

y_train = to_categorical(y_train, num_classes)
y_test = to_categorical(y_test, num_classes)

def lr_schedule(epoch):
    lr = 1e-3 if epoch < 80 else 1e-4
    return lr

def resnet_layer(inputs,
                  num_filters=16,
                  kernel_size=3,
                  strides=1,
                  activation='relu',
                  batch_normalization=True,
                  conv_first=True):

    conv = Conv2D(num_filters,
                  kernel_size=kernel_size,
                  strides=strides,
                  padding='same',
                  kernel_initializer='he_normal',
                  kernel_regularizer=l2(1e-4))

    x = inputs

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if conv_first:
    x = conv(x)
    if batch_normalization:
        x = BatchNormalization()(x)
    if activation is not None:
        x = Activation(activation)(x)
else:
    if batch_normalization:
        x = BatchNormalization()(x)
    if activation is not None:
        x = Activation(activation)(x)
    x = conv(x)
return x

def resnet_v1(input_shape, depth, num_classes=10):

    if (depth - 2) % 6 != 0:
        raise ValueError('depth should be 6n+2 (eg 20, 32, in [a])')
    num_filters = 16
    num_res_blocks = int((depth - 2) / 6)

    inputs = Input(shape=input_shape)
    x = resnet_layer(inputs=inputs)
    for stack in range(3):
        for res_block in range(num_res_blocks):
            strides = 1
            # first layer but not first stack
            if stack > 0 and res_block == 0:
                strides = 2 # downsample
            y = resnet_layer(inputs=x,
                             num_filters=num_filters,
                             strides=strides)
            y = resnet_layer(inputs=y,
                             num_filters=num_filters,
                             activation=None)
            # first layer but not first stack
            if stack > 0 and res_block == 0:
                # linear projection residual shortcut
                # connection to match changed dims
                x = resnet_layer(inputs=x,
                                 num_filters=num_filters,
                                 kernel_size=1,
                                 strides=strides,
                                 activation=None,
                                 batch_normalization=False)

            x = add([x, y])
            x = Activation('relu')(x)
            num_filters *= 2

    # add classifier on top.
    # v1 does not use BN after last shortcut connection-ReLU
    x = AveragePooling2D(pool_size=8)(x)
    y = Flatten()(x)
    outputs = Dense(num_classes,
                    activation='softmax',
                    kernel_initializer='he_normal')(y)

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    # instantiate model.
    model = Model(inputs=inputs, outputs=outputs)
    return model

model = resnet_v1(input_shape=input_shape, depth=depth)

model.compile(loss='categorical_crossentropy',
              optimizer=Adam(lr=lr_schedule(0)),
              metrics=['acc'])
model.summary()

# prepare model saving directory.
save_dir = os.path.join(os.getcwd(), 'saved_models')
model_name = 'cifar10_%s_model.{epoch:03d}.h5' % model_type
if not os.path.isdir(save_dir):
    os.makedirs(save_dir)
filepath = os.path.join(save_dir, model_name)

# prepare callbacks for model saving and for learning rate adjustment.
checkpoint = ModelCheckpoint(filepath=filepath,
                             monitor='val_acc',
                             verbose=1,
                             save_best_only=True)

lr_scheduler = LearningRateScheduler(lr_schedule)

lr_reducer = ReduceLROnPlateau(factor=np.sqrt(0.1),
                               cooldown=0,
                               patience=5,
                               min_lr=0.5e-6)

callbacks = [checkpoint, lr_reducer, lr_scheduler]

# run training, with or without data augmentation.

print('With data augmentation')
datagen = ImageDataGenerator(featurewise_center=False, samplewise_center=
False, featurewise_std_normalization=False,
                             samplewise_std_normalization=False, zca_whit
ening=False, rotation_range=0, width_shift_range=0.1, height_shift_range=0.
1, horizontal_flip=True, vertical_flip=False)

datagen.fit(x_train)

steps_per_epoch = math.ceil(len(x_train) / batch_size)
# fit the model on the batches generated by datagen.flow().
history = model.fit(x=datagen.flow(x_train, y_train, batch_size=batch_si
ze),
                   verbose=1,
                   epochs=epochs,
                   validation_data=(x_test, y_test), ### Testing is done with or
iginal images.
                   steps_per_epoch=steps_per_epoch,

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```
callbacks=callbacks)

# score trained model
scores = model.evaluate(x_test,
                        y_test,
                        batch_size=batch_size,
                        verbose=0)
print('Validation loss:', scores[0])
print('Test accuracy:', scores[1])
```

Model: "functional_1"

Layer (type) connected to	Output Shape	Param #	Connected to
=====			
input_1 (InputLayer)	[(None, 32, 32, 3)]	0	
conv2d (Conv2D) input_1[0][0]	(None, 32, 32, 16)	448	input_1
batch_normalization (BatchNormaliza tion[0][0])	(None, 32, 32, 16)	64	conv2d
activation (Activation) batch_normalization[0][0]	(None, 32, 32, 16)	0	batch_
conv2d_1 (Conv2D) activation[0][0]	(None, 32, 32, 16)	2320	activation
batch_normalization_1 (BatchNormaliza tion[0][0])	(None, 32, 32, 16)	64	conv2d_1
activation_1 (Activation) batch_normalization_1[0][0]	(None, 32, 32, 16)	0	batch_
conv2d_2 (Conv2D) activation_1[0][0]	(None, 32, 32, 16)	2320	activation_1
batch_normalization_2 (BatchNormaliza tion[0][0])	(None, 32, 32, 16)	64	conv2d_2
add (Add) batch_normalization_2[0][0]	(None, 32, 32, 16)	0	activation_2 batch_
activation_2 (Activation) add[0]	(None, 32, 32, 16)	0	add[0]
conv2d_3 (Conv2D) activation_2[0][0]	(None, 32, 32, 16)	2320	activation_2
batch_normalization_3 (BatchNormaliza tion[0][0])	(None, 32, 32, 16)	64	conv2d_3

_3[0][0]

activation_3 (Activation) normalization_3[0][0]	(None, 32, 32, 16)	0	batch_
conv2d_4 (Conv2D) tion_3[0][0]	(None, 32, 32, 16)	2320	activa
batch_normalization_4 (BatchNor _4[0][0]	(None, 32, 32, 16)	64	conv2d
add_1 (Add) tion_2[0][0]	(None, 32, 32, 16)	0	activa
normalization_4[0][0]			batch_
activation_4 (Activation) [0][0]	(None, 32, 32, 16)	0	add_1
conv2d_5 (Conv2D) tion_4[0][0]	(None, 32, 32, 16)	2320	activa
batch_normalization_5 (BatchNor _5[0][0]	(None, 32, 32, 16)	64	conv2d
activation_5 (Activation) normalization_5[0][0]	(None, 32, 32, 16)	0	batch_
conv2d_6 (Conv2D) tion_5[0][0]	(None, 32, 32, 16)	2320	activa
batch_normalization_6 (BatchNor _6[0][0]	(None, 32, 32, 16)	64	conv2d
add_2 (Add) tion_4[0][0]	(None, 32, 32, 16)	0	activa
normalization_6[0][0]			batch_
activation_6 (Activation) [0][0]	(None, 32, 32, 16)	0	add_2
conv2d_7 (Conv2D) tion_6[0][0]	(None, 32, 32, 16)	2320	activa

batch_normalization_7 (BatchNor _7[0][0])	(None, 32, 32, 16)	64	conv2d
activation_7 (Activation) normalization_7[0][0]	(None, 32, 32, 16)	0	batch_
conv2d_8 (Conv2D) tion_7[0][0]	(None, 32, 32, 16)	2320	activa
batch_normalization_8 (BatchNor _8[0][0])	(None, 32, 32, 16)	64	conv2d
add_3 (Add) tion_6[0][0]	(None, 32, 32, 16)	0	activa
normalization_8[0][0]			batch_
activation_8 (Activation) [0][0]	(None, 32, 32, 16)	0	add_3
conv2d_9 (Conv2D) tion_8[0][0]	(None, 32, 32, 16)	2320	activa
batch_normalization_9 (BatchNor _9[0][0])	(None, 32, 32, 16)	64	conv2d
activation_9 (Activation) normalization_9[0][0]	(None, 32, 32, 16)	0	batch_
conv2d_10 (Conv2D) tion_9[0][0]	(None, 32, 32, 16)	2320	activa
batch_normalization_10 (BatchNo _10[0][0])	(None, 32, 32, 16)	64	conv2d
add_4 (Add) tion_8[0][0]	(None, 32, 32, 16)	0	activa
normalization_10[0][0]			batch_
activation_10 (Activation) [0][0]	(None, 32, 32, 16)	0	add_4

conv2d_11 (Conv2D) tion_10[0][0]	(None, 32, 32, 16)	2320	activation_10[0][0]
batch_normalization_11 (Batch Normalization) _11[0][0]	(None, 32, 32, 16)	64	conv2d_11[0][0]
activation_11 (Activation) normalization_11[0][0]	(None, 32, 32, 16)	0	batch_normalization_11[0][0]
conv2d_12 (Conv2D) tion_11[0][0]	(None, 32, 32, 16)	2320	activation_11[0][0]
batch_normalization_12 (Batch Normalization) _12[0][0]	(None, 32, 32, 16)	64	conv2d_12[0][0]
add_5 (Add) tion_10[0][0]	(None, 32, 32, 16)	0	activation_10[0][0]
normalization_12[0][0]			batch_normalization_12[0][0]
activation_12 (Activation) [0][0]	(None, 32, 32, 16)	0	add_5[0][0]
conv2d_13 (Conv2D) tion_12[0][0]	(None, 32, 32, 16)	2320	activation_12[0][0]
batch_normalization_13 (Batch Normalization) _13[0][0]	(None, 32, 32, 16)	64	conv2d_13[0][0]
activation_13 (Activation) normalization_13[0][0]	(None, 32, 32, 16)	0	batch_normalization_13[0][0]
conv2d_14 (Conv2D) tion_13[0][0]	(None, 32, 32, 16)	2320	activation_13[0][0]
batch_normalization_14 (Batch Normalization) _14[0][0]	(None, 32, 32, 16)	64	conv2d_14[0][0]
add_6 (Add) tion_12[0][0]	(None, 32, 32, 16)	0	activation_12[0][0]
normalization_14[0][0]			batch_normalization_14[0][0]

activation_14 (Activation) [0][0]	(None, 32, 32, 16)	0	add_6
conv2d_15 (Conv2D) activation_14[0][0]	(None, 16, 16, 32)	4640	activation_14[0][0]
batch_normalization_15 (Batch Normalization) _15[0][0]	(None, 16, 16, 32)	128	conv2d_15[0][0]
activation_15 (Activation) normalization_15[0][0]	(None, 16, 16, 32)	0	batch_normalization_15[0][0]
conv2d_16 (Conv2D) activation_15[0][0]	(None, 16, 16, 32)	9248	activation_15[0][0]
conv2d_17 (Conv2D) activation_14[0][0]	(None, 16, 16, 32)	544	activation_14[0][0]
batch_normalization_16 (Batch Normalization) _16[0][0]	(None, 16, 16, 32)	128	conv2d_16[0][0]
add_7 (Add) _17[0][0]	(None, 16, 16, 32)	0	conv2d_17[0][0]
batch_normalization_16[0][0]			batch_normalization_16[0][0]
activation_16 (Activation) [0][0]	(None, 16, 16, 32)	0	add_7
conv2d_18 (Conv2D) activation_16[0][0]	(None, 16, 16, 32)	9248	activation_16[0][0]
batch_normalization_17 (Batch Normalization) _18[0][0]	(None, 16, 16, 32)	128	conv2d_18[0][0]
activation_17 (Activation) normalization_17[0][0]	(None, 16, 16, 32)	0	batch_normalization_17[0][0]
conv2d_19 (Conv2D) activation_17[0][0]	(None, 16, 16, 32)	9248	activation_17[0][0]
batch_normalization_18 (Batch Normalization) _19[0][0]	(None, 16, 16, 32)	128	conv2d_19[0][0]

add_8 (Add) tion_16[0][0] normalization_18[0][0]	(None, 16, 16, 32)	0	activation_18 batch_
activation_18 (Activation) [0][0]	(None, 16, 16, 32)	0	add_8
conv2d_20 (Conv2D) tion_18[0][0]	(None, 16, 16, 32)	9248	activation_19
batch_normalization_19 (BatchNo _20[0][0]	(None, 16, 16, 32)	128	conv2d
activation_19 (Activation) normalization_19[0][0]	(None, 16, 16, 32)	0	batch_
conv2d_21 (Conv2D) tion_19[0][0]	(None, 16, 16, 32)	9248	activation_20
batch_normalization_20 (BatchNo _21[0][0]	(None, 16, 16, 32)	128	conv2d
add_9 (Add) tion_18[0][0] normalization_20[0][0]	(None, 16, 16, 32)	0	activation_21 batch_
activation_20 (Activation) [0][0]	(None, 16, 16, 32)	0	add_9
conv2d_22 (Conv2D) tion_20[0][0]	(None, 16, 16, 32)	9248	activation_22
batch_normalization_21 (BatchNo _22[0][0]	(None, 16, 16, 32)	128	conv2d
activation_21 (Activation) normalization_21[0][0]	(None, 16, 16, 32)	0	batch_
conv2d_23 (Conv2D) tion_21[0][0]	(None, 16, 16, 32)	9248	activation_23

batch_normalization_22 (BatchNo	(None, 16, 16, 32)	128	conv2d
_23[0][0]			
add_10 (Add)	(None, 16, 16, 32)	0	activation_20[0][0]
batch_normalization_22[0][0]			
activation_22 (Activation)	(None, 16, 16, 32)	0	add_10[0][0]
conv2d_24 (Conv2D)	(None, 16, 16, 32)	9248	activation_22[0][0]
batch_normalization_23 (BatchNo	(None, 16, 16, 32)	128	conv2d
_24[0][0]			
activation_23 (Activation)	(None, 16, 16, 32)	0	batch_normalization_23[0][0]
conv2d_25 (Conv2D)	(None, 16, 16, 32)	9248	activation_23[0][0]
batch_normalization_24 (BatchNo	(None, 16, 16, 32)	128	conv2d
_25[0][0]			
add_11 (Add)	(None, 16, 16, 32)	0	activation_22[0][0]
batch_normalization_24[0][0]			
activation_24 (Activation)	(None, 16, 16, 32)	0	add_11[0][0]
conv2d_26 (Conv2D)	(None, 16, 16, 32)	9248	activation_24[0][0]
batch_normalization_25 (BatchNo	(None, 16, 16, 32)	128	conv2d
_26[0][0]			
activation_25 (Activation)	(None, 16, 16, 32)	0	batch_normalization_25[0][0]
conv2d_27 (Conv2D)	(None, 16, 16, 32)	9248	activation_25[0][0]

tion_25[0][0]

batch_normalization_26 (BatchNo	(None, 16, 16, 32)	128	conv2d_27[0][0]
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add_12 (Add)	(None, 16, 16, 32)	0	activation_24[0][0]
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batch_normalization_26[0][0]

activation_26 (Activation)	(None, 16, 16, 32)	0	add_12[0][0]
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conv2d_28 (Conv2D)	(None, 16, 16, 32)	9248	activation_26[0][0]
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batch_normalization_27 (BatchNo	(None, 16, 16, 32)	128	conv2d_28[0][0]
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activation_27 (Activation)	(None, 16, 16, 32)	0	batch_normalization_27[0][0]
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conv2d_29 (Conv2D)	(None, 16, 16, 32)	9248	activation_27[0][0]
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batch_normalization_28 (BatchNo	(None, 16, 16, 32)	128	conv2d_29[0][0]
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add_13 (Add)	(None, 16, 16, 32)	0	activation_28[0][0]
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batch_normalization_28[0][0]

activation_28 (Activation)	(None, 16, 16, 32)	0	add_13[0][0]
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conv2d_30 (Conv2D)	(None, 8, 8, 64)	18496	activation_28[0][0]
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batch_normalization_29 (BatchNo	(None, 8, 8, 64)	256	conv2d_30[0][0]
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activation_29 (Activation)	(None, 8, 8, 64)	0	batch_normalization_29[0][0]
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conv2d_31 (Conv2D) tion_29[0][0]	(None, 8, 8, 64)	36928	activation_29[0][0]
conv2d_32 (Conv2D) tion_28[0][0]	(None, 8, 8, 64)	2112	activation_28[0][0]
batch_normalization_30 (Batch Normalization) _31[0][0]	(None, 8, 8, 64)	256	conv2d_31[0][0]
add_14 (Add) _32[0][0] normalization_30[0][0]	(None, 8, 8, 64)	0	conv2d_batch_normalization_30[0][0]
activation_30 (Activation) [0][0]	(None, 8, 8, 64)	0	add_14[0][0]
conv2d_33 (Conv2D) tion_30[0][0]	(None, 8, 8, 64)	36928	activation_30[0][0]
batch_normalization_31 (Batch Normalization) _33[0][0]	(None, 8, 8, 64)	256	conv2d_33[0][0]
activation_31 (Activation) normalization_31[0][0]	(None, 8, 8, 64)	0	batch_normalization_31[0][0]
conv2d_34 (Conv2D) tion_31[0][0]	(None, 8, 8, 64)	36928	activation_31[0][0]
batch_normalization_32 (Batch Normalization) _34[0][0]	(None, 8, 8, 64)	256	conv2d_34[0][0]
add_15 (Add) tion_30[0][0] normalization_32[0][0]	(None, 8, 8, 64)	0	activation_30[0][0] batch_normalization_32[0][0]
activation_32 (Activation) [0][0]	(None, 8, 8, 64)	0	add_15[0][0]
conv2d_35 (Conv2D) tion_32[0][0]	(None, 8, 8, 64)	36928	activation_32[0][0]

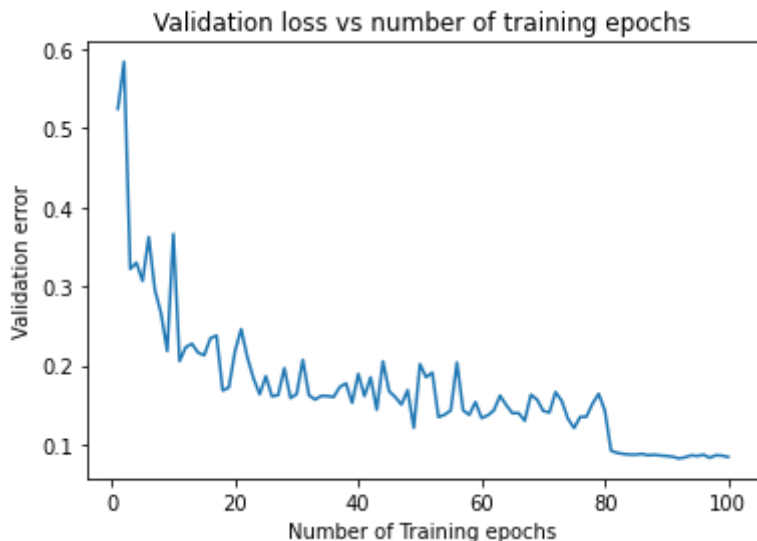
batch_normalization_33 (BatchNo	(None, 8, 8, 64)	256	conv2d_35[0][0]
activation_33 (Activation)	(None, 8, 8, 64)	0	batch_normalization_33[0][0]
conv2d_36 (Conv2D)	(None, 8, 8, 64)	36928	activation_33[0][0]
batch_normalization_34 (BatchNo	(None, 8, 8, 64)	256	conv2d_36[0][0]
add_16 (Add)	(None, 8, 8, 64)	0	activation_32[0][0]
normalization_34[0][0]			batch_normalization_34[0][0]
activation_34 (Activation)	(None, 8, 8, 64)	0	add_16[0][0]
conv2d_37 (Conv2D)	(None, 8, 8, 64)	36928	activation_34[0][0]
batch_normalization_35 (BatchNo	(None, 8, 8, 64)	256	conv2d_37[0][0]
activation_35 (Activation)	(None, 8, 8, 64)	0	batch_normalization_35[0][0]
conv2d_38 (Conv2D)	(None, 8, 8, 64)	36928	activation_35[0][0]
batch_normalization_36 (BatchNo	(None, 8, 8, 64)	256	conv2d_38[0][0]
add_17 (Add)	(None, 8, 8, 64)	0	activation_34[0][0]
normalization_36[0][0]			batch_normalization_36[0][0]
activation_36 (Activation)	(None, 8, 8, 64)	0	add_17[0][0]

conv2d_39 (Conv2D)	(None, 8, 8, 64)	36928	activation_36[0][0]
batch_normalization_37 (Batch Normalization)	(None, 8, 8, 64)	256	conv2d_39[0][0]
activation_37 (Activation)	(None, 8, 8, 64)	0	batch_normalization_37[0][0]
conv2d_40 (Conv2D)	(None, 8, 8, 64)	36928	activation_37[0][0]
batch_normalization_38 (Batch Normalization)	(None, 8, 8, 64)	256	conv2d_40[0][0]
add_18 (Add)	(None, 8, 8, 64)	0	activation_36[0][0]
batch_normalization_38[0][0]			batch_normalization_38[0][0]
activation_38 (Activation)	(None, 8, 8, 64)	0	add_18[0][0]
conv2d_41 (Conv2D)	(None, 8, 8, 64)	36928	activation_38[0][0]
batch_normalization_39 (Batch Normalization)	(None, 8, 8, 64)	256	conv2d_41[0][0]
activation_39 (Activation)	(None, 8, 8, 64)	0	batch_normalization_39[0][0]
conv2d_42 (Conv2D)	(None, 8, 8, 64)	36928	activation_39[0][0]
batch_normalization_40 (Batch Normalization)	(None, 8, 8, 64)	256	conv2d_42[0][0]
add_19 (Add)	(None, 8, 8, 64)	0	activation_38[0][0]
batch_normalization_40[0][0]			batch_normalization_40[0][0]
activation_40 (Activation)	(None, 8, 8, 64)	0	add_19[0][0]

[0][0]

conv2d_43 (Conv2D)	(None, 8, 8, 64)	36928	activation_40[0][0]
batch_normalization_41 (Batch Normalization)	(None, 8, 8, 64)	256	conv2d_43[0][0]
activation_41 (Activation)	(None, 8, 8, 64)	0	batch_normalization_41[0][0]
conv2d_44 (Conv2D)	(None, 8, 8, 64)	36928	activation_41[0][0]
batch_normalization_42 (Batch Normalization)	(None, 8, 8, 64)	256	conv2d_44[0][0]
add_20 (Add)	(None, 8, 8, 64)	0	activation_40[0][0]
normalization_42[0][0]			batch_normalization_42[0][0]
activation_42 (Activation)	(None, 8, 8, 64)	0	add_20[0][0]
average_pooling2d (Average Pooling)	(None, 1, 1, 64)	0	activation_42[0][0]
flatten (Flatten)	(None, 64)	0	average_pooling2d[0][0]
dense (Dense)	(None, 10)	650	flatten[0][0]
=====			
Total params: 665,994			
Trainable params: 662,826			
Non-trainable params: 3,168			
With data augmentation			

```
In [ ]: plt.plot(range(1,101),history.history['val_loss'])[1-el for el in l]
plt.plot(range(1,101),[1-val_acc for val_acc in history.history['val_ac
c']])
plt.xlabel("Number of Training epochs")
plt.ylabel("Validation error")
plt.title("Validation loss vs number of training epochs")
plt.savefig("val_error_without_cutout.png")
plt.show()
```



Q3

```
In [ ]: from google.colab import drive
drive.mount('/content/gdrive')
```

Mounted at /content/gdrive

```
In [ ]: def batch_generator(x, y, epochs, m, batch_size, augment=None):
    for _ in range(epochs):
        n = x.shape[0]
        reorder = np.random.permutation(n)
        cursor = 0
        while cursor + batch_size < x.shape[0]:
            x_batch = x[reorder[cursor:cursor+batch_size]]
            y_batch = y[reorder[cursor:cursor+batch_size]]
            if augment != None:
                yield np.array([augment(xx) for xx in x_batch for rep in
range(m)]), np.array([yy for yy in y_batch for rep in range(m)])
            else:
                yield x_batch, y_batch
            cursor += batch_size
```

```
In [ ]: val_acc_cutout_32 = []
epochs = 50
durations_32 = []
for m in [32]:#4,8,16,32]:
    print("M = ",m)
    model = resnet_v1(
        input_shape=x_train.shape[1:],
        depth=44
    )
    model.compile(
        loss='categorical_crossentropy',
        optimizer=tf.keras.optimizers.RMSprop(),
        metrics=['accuracy']
    )
    duration = time()
    hist = model.fit_generator(
        batch_generator(
            x_train,
            y_train,
            m=m,
            batch_size=64,
            epochs=epochs,
            augment=apply_mask
        ),
        epochs=epochs,
        validation_data=(x_test,y_test),
        steps_per_epoch=np.floor(x_train.shape[0]/64.0),
        verbose=1,
        callbacks=[lr_scheduler]
    )
    durations_32.append(time()-duration)
    val_acc_cutout_32.append(hist.history['val_accuracy'])
    savetxt(F"/content/gdrive/My Drive/val_acc_cutout_32.csv", val_acc_c
utout_32, delimiter=',')
    savetxt(F"/content/gdrive/My Drive/durations_32.csv", durations_32,
delimiter=',')
```

M = 32

WARNING:tensorflow:From <ipython-input-8-fc7985454fd1>:29: Model.fit_generator (from tensorflow.python.keras.engine.training) is deprecated and will be removed in a future version.

Instructions for updating:

Please use Model.fit, which supports generators.

Epoch 1/50

781/781 [=====] - 829s 1s/step - loss: 2.4523
- accuracy: 0.1838 - val_loss: 8.8941 - val_accuracy: 0.1322

Epoch 2/50

781/781 [=====] - 830s 1s/step - loss: 2.2384
- accuracy: 0.2145 - val_loss: 4.9183 - val_accuracy: 0.1734

Epoch 3/50

781/781 [=====] - 829s 1s/step - loss: 2.1764
- accuracy: 0.2276 - val_loss: 6.6778 - val_accuracy: 0.2332

Epoch 4/50

781/781 [=====] - 829s 1s/step - loss: 2.1453
- accuracy: 0.2322 - val_loss: 2.5713 - val_accuracy: 0.2711

Epoch 5/50

781/781 [=====] - 829s 1s/step - loss: 2.1269
- accuracy: 0.2397 - val_loss: 2.1092 - val_accuracy: 0.3123

Epoch 6/50

781/781 [=====] - 828s 1s/step - loss: 2.1124
- accuracy: 0.2445 - val_loss: 2.4620 - val_accuracy: 0.3150

Epoch 7/50

781/781 [=====] - 828s 1s/step - loss: 2.0997
- accuracy: 0.2490 - val_loss: 2.3577 - val_accuracy: 0.2605

Epoch 8/50

781/781 [=====] - 827s 1s/step - loss: 2.0891
- accuracy: 0.2493 - val_loss: 5.9087 - val_accuracy: 0.2397

Epoch 9/50

781/781 [=====] - 826s 1s/step - loss: 2.0797
- accuracy: 0.2545 - val_loss: 2.0752 - val_accuracy: 0.3292

Epoch 10/50

781/781 [=====] - 825s 1s/step - loss: 2.0687
- accuracy: 0.2575 - val_loss: 2.8031 - val_accuracy: 0.3276

Epoch 11/50

781/781 [=====] - 825s 1s/step - loss: 2.0631
- accuracy: 0.2596 - val_loss: 2.5918 - val_accuracy: 0.3336

Epoch 12/50

781/781 [=====] - 824s 1s/step - loss: 2.0532
- accuracy: 0.2662 - val_loss: 2.5565 - val_accuracy: 0.2961

Epoch 13/50

781/781 [=====] - 824s 1s/step - loss: 2.0461
- accuracy: 0.2653 - val_loss: 2.6348 - val_accuracy: 0.2966

Epoch 14/50

781/781 [=====] - 824s 1s/step - loss: 2.0459
- accuracy: 0.2670 - val_loss: 2.5302 - val_accuracy: 0.2901

Epoch 15/50

781/781 [=====] - 823s 1s/step - loss: 2.0346
- accuracy: 0.2690 - val_loss: 1.9890 - val_accuracy: 0.3520

Epoch 16/50

781/781 [=====] - 823s 1s/step - loss: 2.0318
- accuracy: 0.2731 - val_loss: 1.9361 - val_accuracy: 0.3740

Epoch 17/50

781/781 [=====] - 822s 1s/step - loss: 2.0247
- accuracy: 0.2735 - val_loss: 2.2907 - val_accuracy: 0.3718

Epoch 18/50
781/781 [=====] - 822s 1s/step - loss: 2.0208
- accuracy: 0.2789 - val_loss: 1.9534 - val_accuracy: 0.3929

Epoch 19/50
781/781 [=====] - 822s 1s/step - loss: 2.0144
- accuracy: 0.2809 - val_loss: 2.1458 - val_accuracy: 0.3469

Epoch 20/50
781/781 [=====] - 821s 1s/step - loss: 2.0109
- accuracy: 0.2830 - val_loss: 2.5252 - val_accuracy: 0.3701

Epoch 21/50
781/781 [=====] - 820s 1s/step - loss: 2.0052
- accuracy: 0.2815 - val_loss: 2.0140 - val_accuracy: 0.3871

Epoch 22/50
781/781 [=====] - 820s 1s/step - loss: 2.0030
- accuracy: 0.2841 - val_loss: 2.1059 - val_accuracy: 0.3527

Epoch 23/50
781/781 [=====] - 819s 1s/step - loss: 2.0019
- accuracy: 0.2860 - val_loss: 1.9128 - val_accuracy: 0.4005

Epoch 24/50
781/781 [=====] - 819s 1s/step - loss: 1.9959
- accuracy: 0.2885 - val_loss: 1.9944 - val_accuracy: 0.3907

Epoch 25/50
781/781 [=====] - 819s 1s/step - loss: 1.9912
- accuracy: 0.2949 - val_loss: 1.9979 - val_accuracy: 0.3631

Epoch 26/50
781/781 [=====] - 819s 1s/step - loss: 1.9926
- accuracy: 0.2893 - val_loss: 1.9422 - val_accuracy: 0.4047

Epoch 27/50
781/781 [=====] - 819s 1s/step - loss: 1.9837
- accuracy: 0.2917 - val_loss: 2.8312 - val_accuracy: 0.3334

Epoch 28/50
781/781 [=====] - 819s 1s/step - loss: 1.9794
- accuracy: 0.2952 - val_loss: 2.4772 - val_accuracy: 0.3163

Epoch 29/50
781/781 [=====] - 818s 1s/step - loss: 1.9823
- accuracy: 0.2914 - val_loss: 2.1226 - val_accuracy: 0.3424

Epoch 30/50
781/781 [=====] - 817s 1s/step - loss: 1.9852
- accuracy: 0.2925 - val_loss: 2.5434 - val_accuracy: 0.3065

Epoch 31/50
781/781 [=====] - 818s 1s/step - loss: 1.9797
- accuracy: 0.2943 - val_loss: 2.1222 - val_accuracy: 0.3573

Epoch 32/50
781/781 [=====] - 817s 1s/step - loss: 1.9781
- accuracy: 0.2923 - val_loss: 1.8393 - val_accuracy: 0.4118

Epoch 33/50
781/781 [=====] - 817s 1s/step - loss: 1.9791
- accuracy: 0.2973 - val_loss: 1.9869 - val_accuracy: 0.3959

Epoch 34/50
781/781 [=====] - 818s 1s/step - loss: 1.9749
- accuracy: 0.2982 - val_loss: 1.7663 - val_accuracy: 0.4138

Epoch 35/50
781/781 [=====] - 817s 1s/step - loss: 1.9733
- accuracy: 0.2968 - val_loss: 3.0175 - val_accuracy: 0.3076

Epoch 36/50
781/781 [=====] - 817s 1s/step - loss: 1.9675
- accuracy: 0.2999 - val_loss: 2.0879 - val_accuracy: 0.3621

Epoch 37/50
781/781 [=====] - 816s 1s/step - loss: 1.9696
- accuracy: 0.2984 - val_loss: 1.8978 - val_accuracy: 0.3913
Epoch 38/50
781/781 [=====] - 816s 1s/step - loss: 1.9722
- accuracy: 0.2989 - val_loss: 2.2136 - val_accuracy: 0.3519
Epoch 39/50
781/781 [=====] - 816s 1s/step - loss: 1.9663
- accuracy: 0.3034 - val_loss: 2.0892 - val_accuracy: 0.3659
Epoch 40/50
781/781 [=====] - 815s 1s/step - loss: 1.9643
- accuracy: 0.3006 - val_loss: 2.0164 - val_accuracy: 0.3960
Epoch 41/50
781/781 [=====] - 816s 1s/step - loss: 1.9652
- accuracy: 0.2995 - val_loss: 1.9512 - val_accuracy: 0.3843
Epoch 42/50
781/781 [=====] - 815s 1s/step - loss: 1.9642
- accuracy: 0.3009 - val_loss: 2.1837 - val_accuracy: 0.3738
Epoch 43/50
781/781 [=====] - 816s 1s/step - loss: 1.9620
- accuracy: 0.3045 - val_loss: 1.9665 - val_accuracy: 0.4092
Epoch 44/50
626/781 [=====>.....] - ETA: 2:41 - loss: 1.9645 - a
ccuracy: 0.3018

```

In [ ]: val_acc_cutout_16 = []
epochs = 50
durations_16 = []
for m in [16]:#,4,8,16,32]:
    print("M = ",m)
    model = resnet_v1(
        input_shape=x_train.shape[1:],
        depth=44
    )
    model.compile(
        loss='categorical_crossentropy',
        optimizer=tf.keras.optimizers.RMSprop(),
        metrics=['accuracy']
    )
    duration = time()
    hist = model.fit_generator(
        batch_generator(
            x_train,
            y_train,
            m=m,
            batch_size=64,
            epochs=epochs,
            augment=apply_mask
        ),
        epochs=epochs,
        validation_data=(x_test,y_test),
        steps_per_epoch=np.floor(x_train.shape[0]/64.0),
        verbose=1,
        callbacks=[lr_scheduler]
    )
    durations_16.append(time()-duration)
    val_acc_cutout_16.append(hist.history['val_accuracy'])
    savetxt(F"/content/gdrive/My Drive/val_acc_cutout_16.csv", val_acc_c
utout_16, delimiter=',')
    savetxt(F"/content/gdrive/My Drive/durations_16.csv", durations_16,
delimiter=',')

```

```
M = 16
Epoch 1/50
781/781 [=====] - 351s 449ms/step - loss: 2.32
46 - accuracy: 0.2588 - val_loss: 2.2616 - val_accuracy: 0.3234
Epoch 2/50
781/781 [=====] - 350s 449ms/step - loss: 2.04
90 - accuracy: 0.3229 - val_loss: 2.1283 - val_accuracy: 0.3616
Epoch 3/50
781/781 [=====] - 350s 449ms/step - loss: 1.94
08 - accuracy: 0.3497 - val_loss: 2.0421 - val_accuracy: 0.3785
Epoch 4/50
781/781 [=====] - 350s 448ms/step - loss: 1.86
49 - accuracy: 0.3729 - val_loss: 2.7860 - val_accuracy: 0.3220
Epoch 5/50
781/781 [=====] - 350s 448ms/step - loss: 1.82
32 - accuracy: 0.3830 - val_loss: 2.3621 - val_accuracy: 0.3577
Epoch 6/50
781/781 [=====] - 350s 448ms/step - loss: 1.78
54 - accuracy: 0.3984 - val_loss: 1.6221 - val_accuracy: 0.4752
Epoch 7/50
781/781 [=====] - 350s 448ms/step - loss: 1.76
37 - accuracy: 0.4010 - val_loss: 1.6932 - val_accuracy: 0.4996
Epoch 8/50
781/781 [=====] - 349s 447ms/step - loss: 1.73
94 - accuracy: 0.4123 - val_loss: 1.7524 - val_accuracy: 0.4478
Epoch 9/50
781/781 [=====] - 349s 447ms/step - loss: 1.71
35 - accuracy: 0.4251 - val_loss: 1.6910 - val_accuracy: 0.5094
Epoch 10/50
781/781 [=====] - 349s 447ms/step - loss: 1.70
26 - accuracy: 0.4257 - val_loss: 1.5577 - val_accuracy: 0.5254
Epoch 11/50
781/781 [=====] - 348s 446ms/step - loss: 1.68
17 - accuracy: 0.4315 - val_loss: 1.8206 - val_accuracy: 0.4660
Epoch 12/50
781/781 [=====] - 349s 446ms/step - loss: 1.66
57 - accuracy: 0.4375 - val_loss: 1.5431 - val_accuracy: 0.5336
Epoch 13/50
781/781 [=====] - 349s 447ms/step - loss: 1.65
12 - accuracy: 0.4481 - val_loss: 1.4617 - val_accuracy: 0.5694
Epoch 14/50
781/781 [=====] - 349s 446ms/step - loss: 1.63
95 - accuracy: 0.4476 - val_loss: 1.5714 - val_accuracy: 0.5230
Epoch 15/50
781/781 [=====] - 348s 446ms/step - loss: 1.63
19 - accuracy: 0.4519 - val_loss: 1.5047 - val_accuracy: 0.5651
Epoch 16/50
781/781 [=====] - 348s 446ms/step - loss: 1.61
73 - accuracy: 0.4575 - val_loss: 1.6193 - val_accuracy: 0.5502
Epoch 17/50
781/781 [=====] - 348s 446ms/step - loss: 1.60
67 - accuracy: 0.4612 - val_loss: 1.5089 - val_accuracy: 0.5654
Epoch 18/50
781/781 [=====] - 348s 445ms/step - loss: 1.60
18 - accuracy: 0.4649 - val_loss: 1.5367 - val_accuracy: 0.5813
Epoch 19/50
781/781 [=====] - 348s 445ms/step - loss: 1.58
```

78 - accuracy: 0.4711 - val_loss: 1.6740 - val_accuracy: 0.5736
Epoch 20/50
781/781 [=====] - 348s 445ms/step - loss: 1.58
46 - accuracy: 0.4719 - val_loss: 1.6035 - val_accuracy: 0.5435
Epoch 21/50
781/781 [=====] - 348s 445ms/step - loss: 1.57
36 - accuracy: 0.4766 - val_loss: 1.1968 - val_accuracy: 0.6278
Epoch 22/50
781/781 [=====] - 347s 445ms/step - loss: 1.56
89 - accuracy: 0.4775 - val_loss: 1.4297 - val_accuracy: 0.5711
Epoch 23/50
781/781 [=====] - 347s 444ms/step - loss: 1.56
27 - accuracy: 0.4785 - val_loss: 1.7105 - val_accuracy: 0.5409
Epoch 24/50
781/781 [=====] - 347s 444ms/step - loss: 1.55
19 - accuracy: 0.4854 - val_loss: 1.3900 - val_accuracy: 0.6067
Epoch 25/50
781/781 [=====] - 347s 445ms/step - loss: 1.54
58 - accuracy: 0.4877 - val_loss: 1.9125 - val_accuracy: 0.4994
Epoch 26/50
781/781 [=====] - 347s 444ms/step - loss: 1.54
20 - accuracy: 0.4887 - val_loss: 1.4997 - val_accuracy: 0.5893
Epoch 27/50
781/781 [=====] - 347s 444ms/step - loss: 1.53
69 - accuracy: 0.4927 - val_loss: 1.4546 - val_accuracy: 0.5820
Epoch 28/50
781/781 [=====] - 347s 444ms/step - loss: 1.53
09 - accuracy: 0.4955 - val_loss: 1.6628 - val_accuracy: 0.5456
Epoch 29/50
781/781 [=====] - 347s 444ms/step - loss: 1.53
04 - accuracy: 0.4930 - val_loss: 1.2704 - val_accuracy: 0.6084
Epoch 30/50
781/781 [=====] - 347s 444ms/step - loss: 1.52
04 - accuracy: 0.4970 - val_loss: 1.1398 - val_accuracy: 0.6452
Epoch 31/50
781/781 [=====] - 347s 445ms/step - loss: 1.51
85 - accuracy: 0.4994 - val_loss: 1.5247 - val_accuracy: 0.6070
Epoch 32/50
781/781 [=====] - 347s 444ms/step - loss: 1.51
22 - accuracy: 0.5016 - val_loss: 1.4050 - val_accuracy: 0.6199
Epoch 33/50
781/781 [=====] - 346s 443ms/step - loss: 1.50
90 - accuracy: 0.5023 - val_loss: 1.3357 - val_accuracy: 0.6294
Epoch 34/50
781/781 [=====] - 346s 443ms/step - loss: 1.50
56 - accuracy: 0.5081 - val_loss: 1.1745 - val_accuracy: 0.6539
Epoch 35/50
781/781 [=====] - 346s 443ms/step - loss: 1.49
39 - accuracy: 0.5117 - val_loss: 1.3223 - val_accuracy: 0.6173
Epoch 36/50
781/781 [=====] - 346s 443ms/step - loss: 1.49
47 - accuracy: 0.5100 - val_loss: 1.2596 - val_accuracy: 0.6382
Epoch 37/50
781/781 [=====] - 346s 443ms/step - loss: 1.49
38 - accuracy: 0.5102 - val_loss: 1.2548 - val_accuracy: 0.6551
Epoch 38/50
781/781 [=====] - 346s 443ms/step - loss: 1.48

```

31 - accuracy: 0.5154 - val_loss: 1.1847 - val_accuracy: 0.6446
Epoch 39/50
781/781 [=====] - 345s 442ms/step - loss: 1.47
91 - accuracy: 0.5155 - val_loss: 1.4447 - val_accuracy: 0.5813
Epoch 40/50
781/781 [=====] - 346s 443ms/step - loss: 1.47
77 - accuracy: 0.5169 - val_loss: 1.4787 - val_accuracy: 0.6207
Epoch 41/50
781/781 [=====] - 346s 443ms/step - loss: 1.47
78 - accuracy: 0.5175 - val_loss: 1.3247 - val_accuracy: 0.6319
Epoch 42/50
781/781 [=====] - 346s 443ms/step - loss: 1.47
60 - accuracy: 0.5188 - val_loss: 1.4403 - val_accuracy: 0.5875
Epoch 43/50
781/781 [=====] - 347s 444ms/step - loss: 1.47
48 - accuracy: 0.5198 - val_loss: 1.4437 - val_accuracy: 0.6266
Epoch 44/50
781/781 [=====] - 346s 443ms/step - loss: 1.46
64 - accuracy: 0.5228 - val_loss: 1.1758 - val_accuracy: 0.6656
Epoch 45/50
781/781 [=====] - 346s 443ms/step - loss: 1.46
53 - accuracy: 0.5227 - val_loss: 1.6002 - val_accuracy: 0.5752
Epoch 46/50
781/781 [=====] - 346s 443ms/step - loss: 1.45
52 - accuracy: 0.5282 - val_loss: 1.3545 - val_accuracy: 0.6496
Epoch 47/50
781/781 [=====] - 346s 442ms/step - loss: 1.45
92 - accuracy: 0.5273 - val_loss: 1.1042 - val_accuracy: 0.6927
Epoch 48/50
781/781 [=====] - 345s 441ms/step - loss: 1.45
77 - accuracy: 0.5270 - val_loss: 1.2462 - val_accuracy: 0.6345
Epoch 49/50
781/781 [=====] - 345s 441ms/step - loss: 1.45
10 - accuracy: 0.5285 - val_loss: 1.0942 - val_accuracy: 0.6727
Epoch 50/50
781/781 [=====] - 345s 441ms/step - loss: 1.45
32 - accuracy: 0.5278 - val_loss: 1.3246 - val_accuracy: 0.6311

```

```

In [14]: cutout2_data = loadtxt("val_acc_cutout_2.csv",delimiter=",")
cutout4_data = loadtxt("val_acc_cutout_4.csv",delimiter=",")
cutout8_data = loadtxt("val_acc_cutout_8.csv",delimiter=",")
cutout16_data = loadtxt("val_acc_cutout_16.csv",delimiter=",")
cutout32_data = loadtxt("val_acc_cutout_32.csv",delimiter=",")

durations2_data = loadtxt("durations_2.csv",delimiter=",")
durations4_data = loadtxt("durations_4.csv",delimiter=",")
durations8_data = loadtxt("durations_8.csv",delimiter=",")
durations16_data = loadtxt("durations_16.csv",delimiter=",")
durations32_data = loadtxt("durations_32.csv",delimiter=",")

```

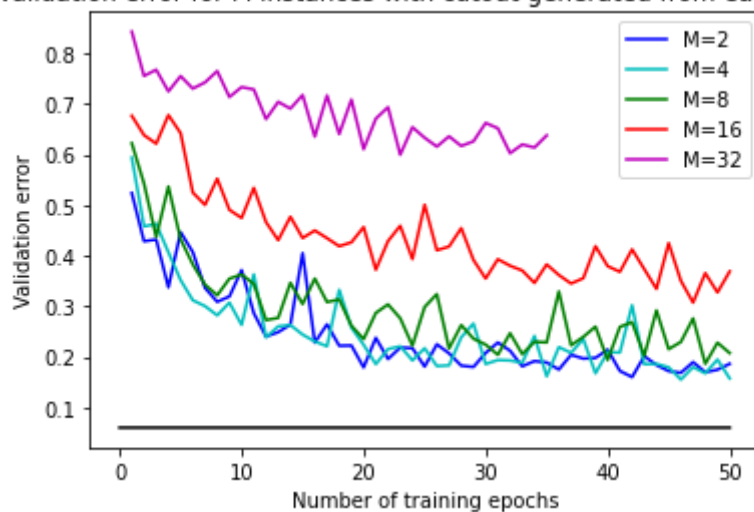
```

In [13]: def val_error(val):
          return [1-v for v in val]

plt.plot(range(1,51),val_error(cutout2_data),"b-")
plt.plot(range(1,51),val_error(cutout4_data),"c-")
plt.plot(range(1,51),val_error(cutout8_data),"g-")
plt.plot(range(1,51),val_error(cutout16_data),"r-")
plt.plot(range(1,36),val_error(cutout32_data),"m-")
plt.xlabel("Number of training epochs")
plt.ylabel("Validation error")
plt.legend(["M=2", "M=4", "M=8", "M=16", "M=32"])
plt.plot(np.linspace(0,50,10000),[0.06]*10000,"k-")
plt.title("Validation error for M instances with cutout generated from each input")
#plt.savefig("val_error_with_cutout.png")
plt.show()

```

Validation error for M instances with cutout generated from each input



```

In [20]: print (" M=2 Time to train 50 epochs :", durations2_data,"\n")
          print (" M=4 Time to train 50 epochs :", durations4_data,"\n")
          print (" M=8 Time to train 50 epochs :", durations8_data,"\n")
          print (" M=16 Time to train 50 epochs :", durations16_data,"\n")
          print (" M=32 Time to train 35 epochs :", durations32_data,"\n")

```

M=2 Time to train 50 epochs : 2766.2118268013

M=4 Time to train 50 epochs : 4897.306997060776

M=8 Time to train 50 epochs : 9115.753979206085

M=16 Time to train 50 epochs : 17399.752579927444

M=32 Time to train 35 epochs : 23586.50715637207

I could not train them for 100 epochs as I got runtime error on both colab and Jupyterhub but I trained them for 50 epochs for $M=2$ to 16 and 35 epochs for $M=32$.

In []: