Adversarially trained autoencoder

In part 1, we train an autoencoder using mean-squared-error (mse).
In part 2, we couple the same autoencoder to a discriminator similar to one use for a GAN and train the autoencoder using mse on images plus binary cross entropy on the discriminator loss.

We will train our GAN on images from CIFAR10, a dataset of 50,000 32x32 RGB images belong to 10 classes (5,000 images per class). To make things even easier, we will only use images belonging to the class "frog".

Part 1:

Schematically, the autoencoder looks like this:

- An `encoder` network maps images of shape `(32, 32, 3)` to vectors of shape `(latent_dim,)`.
- A `decoder` network maps vectors of shape `(latent_dim,)` to images of shape `(32, 32, 3)`.
- An `autoencoder` network chains these together to give `ae_image = decoder(autoencoder(x))`

In part 1, this autoencoder is trained to reproduce images, using mse loss.

The autoencoder

First, develop an `autoencoder` model.

- You may use any network structure that you like, **subject to a maximum of 4 million trainable parameters and a latent dimension of 32.**
- It should input a batch of images of shape (32,32,3), funnel down to a batch of vectors 32 dimensional space, and reconstruct back to a batch of images of the same size as the original.
- You may make separate encoder and decoder models and chain them or make a single model. If you use separate models, you should show the summary for each plus the summary for the full model.

Use `autoencoder` as the name of your full model, and use `autoencoder.summary()` to show the structure of your autoencoder.

The final activation should be a sigmoid to provide output values in the range 0 to 1 to create a valid image.

In [1]:
```
import keras
from keras.models import Sequential
from keras.layers import Reshape, Flatten, Dense, Conv2D, Conv2DTranspose, Batc
hNormalization
import numpy as np

latent_dim = 32
height = 32
width = 32
channels = 3

img_input = keras.Input(shape=(height, width, channels))

# Your network here to connect img_input to img_output
encoder = Sequential()
encoder.add(Conv2D(8, (7,7), activation='sigmoid', input_shape=(32,32,3)))
encoder.add(BatchNormalization())
encoder.add(Conv2D(16, (5,5), activation='sigmoid', input_shape=(26,26,8)))
encoder.add(BatchNormalization())
encoder.add(Conv2D(32, (3,3), activation='sigmoid', input_shape=(22,22,16)))
encoder.add(BatchNormalization())
encoder.add(Flatten())
encoder.add(Dense(32, activation='sigmoid'))
encoder.add(BatchNormalization())
encoder.add(Dense(32, activation='sigmoid'))

decoder = Sequential()
decoder.add(Dense(32, activation='sigmoid'))
decoder.add(BatchNormalization())
decoder.add(Dense(20*20*32, activation='sigmoid'))
decoder.add(BatchNormalization())
decoder.add(Reshape((20,20,32)))
decoder.add(Conv2DTranspose(16, (3,3), activation='sigmoid', input_shape=(20,20
,32)))
decoder.add(BatchNormalization())
decoder.add(Conv2DTranspose(8, (5,5), activation='sigmoid', input_shape=(22,22,
16)))
decoder.add(BatchNormalization())
decoder.add(Conv2DTranspose(3, (7,7), activation='sigmoid', input_shape=(26,26,
8)))

autoencoder = Sequential()
autoencoder.add(encoder)
autoencoder.add(decoder)
autoencoder.summary()
autoencoder.compile(optimizer='rmsprop', loss='mse')
```

```
Using TensorFlow backend.
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
sequential_1 (Sequential)    (None, 32)                420080
_________________________________________________________________
sequential_2 (Sequential)    (None, 32, 32, 3)         483891
=================================================================
Total params: 903,971
Trainable params: 878,083
Non-trainable params: 25,888
_________________________________________________________________
```

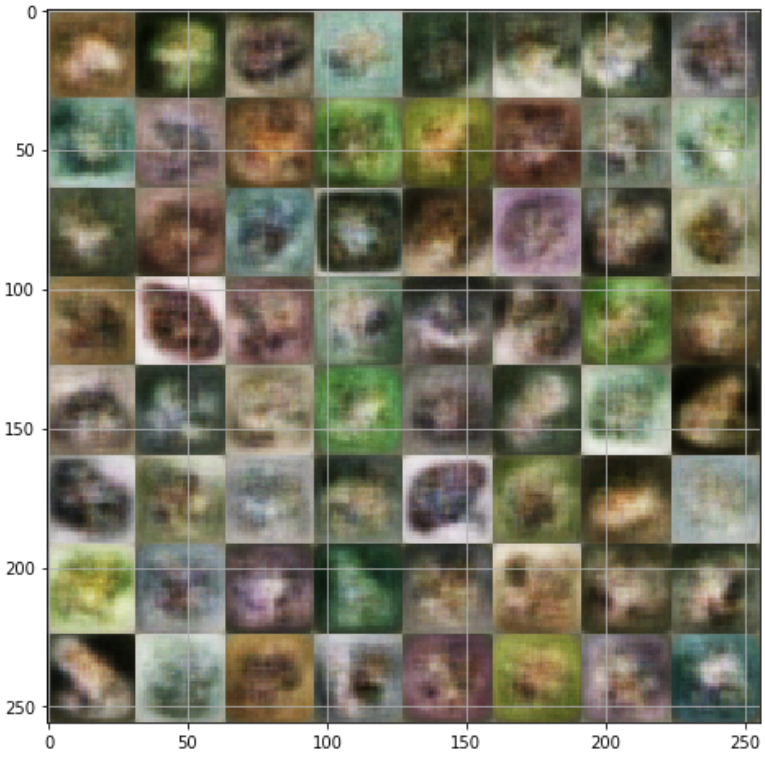
Here is some code to load the data and display images.

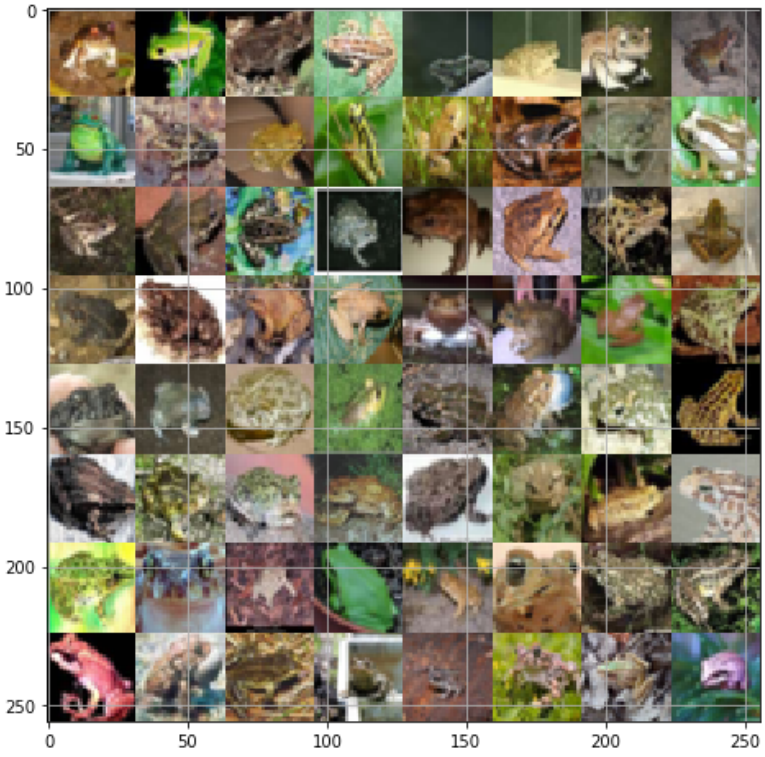
In [2]:
```
# Load CIFAR10 data
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()

# Select frog images (class 6)
x_train = x_train[y_train.flatten() == 6]
x_test = x_test[y_test.flatten() == 6]

# Normalize data
x_train = x_train.reshape(
    (x_train.shape[0],) + (height, width, channels)).astype('float32') / 255.
x_test = x_test.reshape(
    (x_test.shape[0],) + (height, width, channels)).astype('float32') / 255.


import matplotlib.pyplot as plt

# input a tensor of shape (num_images, x_size, y_size, channels)
# channels is 1 for greyscale and 3 for color images
def show_images(images):
  # Display tiled images
  n_x = np.int(np.sqrt(images.shape[0]))
  n_y = np.int(np.ceil(images.shape[0]/n_x))
  tile_x = images.shape[1]
  tile_y = images.shape[2]
  figure = np.zeros((tile_x * n_x, tile_y * n_y, images.shape[3]))

  for i in range(n_x):
    for j in range(n_y):
      cur_ind = i+n_x*j
      if (cur_ind >= images.shape[0]):
        break
      cur_image = images[cur_ind, :,:,:]
      figure[i * tile_x: (i + 1) * tile_x,
         j * tile_y: (j + 1) * tile_y] = cur_image

  plt.figure(figsize=(n_x, n_y))
  plt.imshow(np.squeeze(figure))
  ax = plt.gca()
  ax.grid(b=None)

  plt.show()
```

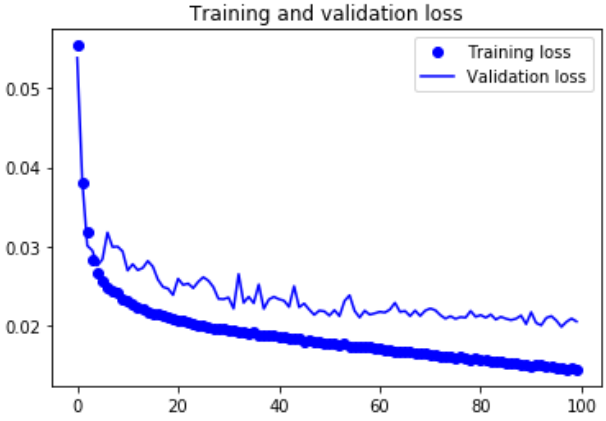
Train your autoencoder for 100 epochs and display reconstructed and real images and training history. **You should be able to get validation loss below 0.02.**

In [3]:
```
num_epochs = 100
history = autoencoder.fit(x_train, x_train,
                epochs=num_epochs,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test, x_test))

ae_images = autoencoder.predict(x_train[0:64])
show_images(ae_images)
show_images(x_train[0:64])

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(loss))

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```

```
Train on 5000 samples, validate on 1000 samples
Epoch 1/100
5000/5000 [==============================] - 59s 12ms/step - loss: 0.0554 - val
_loss: 0.0539
Epoch 2/100
5000/5000 [==============================] - 57s 11ms/step - loss: 0.0381 - val
_loss: 0.0383
Epoch 3/100
5000/5000 [==============================] - 56s 11ms/step - loss: 0.0318 - val
_loss: 0.0301
Epoch 4/100
5000/5000 [==============================] - 55s 11ms/step - loss: 0.0284 - val
_loss: 0.0295
Epoch 5/100
5000/5000 [==============================] - 56s 11ms/step - loss: 0.0266 - val
_loss: 0.0276
Epoch 6/100
5000/5000 [==============================] - 56s 11ms/step - loss: 0.0257 - val
_loss: 0.0283
Epoch 7/100
5000/5000 [==============================] - 57s 11ms/step - loss: 0.0248 - val
_loss: 0.0317
Epoch 8/100
5000/5000 [==============================] - 56s 11ms/step - loss: 0.0244 - val
_loss: 0.0299
Epoch 9/100
5000/5000 [==============================] - 57s 11ms/step - loss: 0.0240 - val
_loss: 0.0300
Epoch 10/100
5000/5000 [==============================] - 56s 11ms/step - loss: 0.0233 - val
_loss: 0.0294
Epoch 11/100
5000/5000 [==============================] - 57s 11ms/step - loss: 0.0230 - val
_loss: 0.0269
Epoch 12/100
5000/5000 [==============================] - 56s 11ms/step - loss: 0.0228 - val
_loss: 0.0277
Epoch 13/100
5000/5000 [==============================] - 58s 12ms/step - loss: 0.0224 - val
_loss: 0.0270
Epoch 14/100
5000/5000 [==============================] - 57s 11ms/step - loss: 0.0220 - val
_loss: 0.0273
Epoch 15/100
5000/5000 [==============================] - 56s 11ms/step - loss: 0.0217 - val
_loss: 0.0281
Epoch 16/100
5000/5000 [==============================] - 57s 11ms/step - loss: 0.0214 - val
_loss: 0.0274
Epoch 17/100
5000/5000 [==============================] - 56s 11ms/step - loss: 0.0214 - val
_loss: 0.0258
Epoch 18/100
5000/5000 [==============================] - 57s 11ms/step - loss: 0.0213 - val
_loss: 0.0248
Epoch 19/100
5000/5000 [==============================] - 57s 11ms/step - loss: 0.0210 - val
_loss: 0.0246
Epoch 20/100
5000/5000 [==============================] - 57s 11ms/step - loss: 0.0209 - val
_loss: 0.0238
Epoch 21/100
5000/5000 [==============================] - 56s 11ms/step - loss: 0.0206 - val
```


0
50
100
150
200
250
0
50
100
150
200
250


0
50
100
150
200
250
0
50
100
150
200
250


Training and validation loss
Training loss
Validation loss
0.05
0.04
0.03
0.02
0
20
40
60
80
100

Adversarially trained autoencoder

Part 2:

In part 2, we add the adversarial part by coupling the autoencoder with a discriminator.

- A `discriminator` network maps images of shape (32, 32, 3) to a binary score estimating the probability that the image is real.
- A `gan` network chains the generator and the discriminator together: `gan(x) = discriminator(autoencoder(x))` . Thus this `gan` network maps latent space vectors to the discriminator's assessment of the realism of these latent vectors as decoded by the generator.

We train the autoencoder using a weighted sum of the mse loss and binary cross entropy on the output of the discriminator.

To do this, the gan will need to have two outputs and two loss functions that are combined via a weighted sum. There is documentation about that here: multi-input-and-multi-output-models (https://keras.io/getting-started/functional-api-guide/#multi-input-and-multi-output-models)

In alternation, we train the discriminator using examples of real and fake images along with "real"/"fake" labels, as we would train any regular image classification model. This uses binary cross entropy loss.

The autoencoder

Use the same autoencoder structure from part 1. Do not use a saved version of that autoencoder - just use the same structure, but start with an untrained model. One of the points of this assignment is to compare the results of training with mse versus training with mse plus adversarial loss.

In [0]:

In [0]:
```
import keras
from keras import layers
from keras.models import Sequential, Model
from keras.layers import Input, Reshape, Flatten, Dense, Conv2D, Conv2DTranspos
e, BatchNormalization
import numpy as np

latent_dim = 32
height = 32
width = 32
channels = 3

img_input = keras.Input(shape=(height, width, channels))

# Your network here to connect img_input to img_output
encoder = Sequential()
encoder.add(Conv2D(8, (7,7), activation='sigmoid', input_shape=(32,32,3)))
encoder.add(BatchNormalization())
encoder.add(Conv2D(16, (5,5), activation='sigmoid', input_shape=(26,26,8)))
encoder.add(BatchNormalization())
encoder.add(Conv2D(32, (3,3), activation='sigmoid', input_shape=(22,22,16)))
encoder.add(BatchNormalization())
encoder.add(Flatten())
encoder.add(Dense(32, activation='sigmoid'))
encoder.add(BatchNormalization())
encoder.add(Dense(32, activation='sigmoid'))

decoder = Sequential()
decoder.add(Dense(32, activation='sigmoid'))
decoder.add(BatchNormalization())
decoder.add(Dense(20*20*32, activation='sigmoid'))
decoder.add(BatchNormalization())
decoder.add(Reshape((20,20,32)))
decoder.add(Conv2DTranspose(16, (3,3), activation='sigmoid', input_shape=(20,20
,32)))
decoder.add(BatchNormalization())
decoder.add(Conv2DTranspose(8, (5,5), activation='sigmoid', input_shape=(22,22,
16)))
decoder.add(BatchNormalization())
decoder.add(Conv2DTranspose(3, (7,7), activation='sigmoid', input_shape=(26,26,
8)))

autoencoder = Sequential()
autoencoder.add(encoder)
autoencoder.add(decoder)

autoencoder.summary()
autoencoder.compile(optimizer='rmsprop', loss='mse')
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
sequential_9 (Sequential)    (None, 32)                420080
_________________________________________________________________
sequential_10 (Sequential)   (None, 32, 32, 3)         483891
=================================================================
Total params: 903,971
Trainable params: 878,083
Non-trainable params: 25,888
_________________________________________________________________
```

Here is some code to load the data and display images.

In [0]:
```
# Load CIFAR10 data
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()

# Select frog images (class 6)
x_train = x_train[y_train.flatten() == 6]
x_test = x_test[y_test.flatten() == 6]

# Normalize data
x_train = x_train.reshape(
    (x_train.shape[0],) + (height, width, channels)).astype('float32') / 255.
x_test = x_test.reshape(
    (x_test.shape[0],) + (height, width, channels)).astype('float32') / 255.

import matplotlib.pyplot as plt

# input a tensor of shape (num_images, x_size, y_size, channels)
# channels is 1 for greyscale and 3 for color images
def show_images(images):
  # Display tiled images
  n_x = np.int(np.sqrt(images.shape[0]))
  n_y = np.int(np.ceil(images.shape[0]/n_x))
  tile_x = images.shape[1]
  tile_y = images.shape[2]
  figure = np.zeros((tile_x * n_x, tile_y * n_y, images.shape[3]))

  for i in range(n_x):
    for j in range(n_y):
      cur_ind = i+n_x*j
      if (cur_ind >= images.shape[0]):
        break
      cur_image = images[cur_ind, :,:,:]
      figure[i * tile_x: (i + 1) * tile_x,
         j * tile_y: (j + 1) * tile_y] = cur_image

  plt.figure(figsize=(n_x, n_y))
  plt.imshow(np.squeeze(figure))
  ax = plt.gca()
  ax.grid(b=None)

  plt.show()
```

The discriminator

Then, we develop a `discriminator` model, that takes as input a candidate image (real or synthetic) and classifies it into one of two classes, either "generated image" or "real image that comes from the training set".

In [0]:
```
discriminator_input = layers.Input(shape=(height, width, channels))

# Your code here for the discriminator
# There is one example of a discriminator in Deep Learning with Python, section
8.5

# Your discriminator should end with the final binary classification layer:

#discriminator_output = Dense(1, activation='sigmoid')(x)
discriminator = Sequential()
discriminator.add(Conv2D(8, (7,7), activation='sigmoid', input_shape=(32,32,3))
)
discriminator.add(BatchNormalization())
discriminator.add(Conv2D(16, (5,5), activation='sigmoid', input_shape=(26,26,8)
))
discriminator.add(BatchNormalization())
discriminator.add(Conv2D(32, (3,3), activation='sigmoid', input_shape=(22,22,16
)))
discriminator.add(BatchNormalization())
discriminator.add(Conv2D(64, (3,3), activation='sigmoid', input_shape=(20,20,32
)))
discriminator.add(BatchNormalization())
discriminator.add(Flatten())
discriminator.add(Dense(64, activation='sigmoid'))
discriminator.add(BatchNormalization())
discriminator.add(Dense(1, activation='sigmoid'))

# discriminator = keras.models.Model(discriminator_input, discriminator_output)
discriminator.summary()

# To stabilize training, we use learning rate decay
# and gradient clipping (by value) in the optimizer.
discriminator_optimizer = keras.optimizers.RMSprop(lr=0.0008, clipvalue=1.0, de
cay=1e-8)
discriminator.compile(optimizer=discriminator_optimizer, loss='binary_crossentr
opy')
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_18 (Conv2D)           (None, 26, 26, 8)         1184      
_________________________________________________________________
batch_normalization_35 (Batc (None, 26, 26, 8)         32        
_________________________________________________________________
conv2d_19 (Conv2D)           (None, 22, 22, 16)        3216      
_________________________________________________________________
batch_normalization_36 (Batc (None, 22, 22, 16)        64        
_________________________________________________________________
conv2d_20 (Conv2D)           (None, 20, 20, 32)        4640      
_________________________________________________________________
batch_normalization_37 (Batc (None, 20, 20, 32)        128       
_________________________________________________________________
conv2d_21 (Conv2D)           (None, 18, 18, 64)        18496     
_________________________________________________________________
batch_normalization_38 (Batc (None, 18, 18, 64)        256       
_________________________________________________________________
flatten_6 (Flatten)          (None, 20736)             0         
_________________________________________________________________
dense_17 (Dense)             (None, 64)                1327168   
_________________________________________________________________
batch_normalization_39 (Batc (None, 64)                256       
_________________________________________________________________
dense_18 (Dense)             (None, 1)                 65        
=================================================================
Total params: 1,355,505
Trainable params: 1,355,137
Non-trainable params: 368
_________________________________________________________________
```

The adversarial network

Finally, we setup an adversarial network (AN) that chains the autoencoder and the discriminator. This will move the autoencoder in a direction that improves its ability to fool the discriminator while still reproducing its input. The AN is meant to be trained with labels that are always "these are real images", so the weights of `autoencoder` will be updated to make `discriminator` more likely to predict "real" when looking at fake images. Very importantly, we set the discriminator to be frozen during training (non-trainable): its weights will not be updated when training `gan`. If the discriminator weights could be updated during this process, then we would be training the discriminator to always predict "real", which is not what we want!

Note: Setting nontrainable weights may give a warning about a mismatch between trainable and nontrainable weights, but you may ignore that.

You will need to set up your model to have a loss function that is a weighted sum of the mse on the autoencoder and the binary cross entropy from the discriminator. The link in the introduction gives information about how to do that.

Training you AN

Now we can start training. To recapitulate, this is schematically what the training loop looks like:

''' for each epoch:

```
    * Draw a batch of training images
    * Reconstruct images with `autoencoder`
    * Mix the generated images with real ones.
    * Train `discriminator` using these mixed images, with corresponding targets, either
    "real" (for the real images) or "fake" (for the generated images).
    * Draw new random images.
    * Train `gan` using these random images, with targets that all say "these are real im
    ages". This will update the weights of the autoencoder (only, since discriminator is
    frozen inside `an`) to move them towards getting the discriminator to predict "these
    are real images" for generated images, i.e. this trains the autoencoder to fool the d
    iscriminator.
```

'''

The code below does most of this. You'll need to set up the training on batches. You should also find a way to get and plot the validation loss - the loss on the test data. This is not included below.

In [0]:
```
# Set discriminator weights to non-trainable
# (will only apply to the `gan` model)
discriminator.trainable = False

# Set up the gan to output both the image and the real/fake value from the disc
riminator
# See https://keras.io/getting-started/functional-api-guide/#multi-input-and-mu
lti-output-models

inputs = Input(shape=(32,32,3))
x = encoder(inputs)
img = decoder(x)
prob = discriminator(img)
gan = Model(inputs=inputs, outputs=[img,prob])

# loss = { "img": "mse", "prob": "categorical_crossentropy", }
# loss_weights = { "img": 1.0, "prob": 1.0 }
loss = ["mse", "binary_crossentropy"]
loss_weights=[1.0, 0.1]
gan_optimizer = keras.optimizers.RMSprop(lr=0.0004, clipvalue=1.0, decay=1e-8)
gan.compile(optimizer=gan_optimizer, loss=loss, loss_weights=loss_weights)
```

In [0]:
```
batch_size = 128
num_epochs = 100

print('Number of epochs = ' + str(num_epochs))

adv_loss = np.zeros((num_epochs, 3))
val_adv_loss = np.zeros((num_epochs, 3))
disc_loss = np.zeros((num_epochs, 1))

max_ind = x_train.shape[0]
# Start training loop
start = 0
epoch = 0
while epoch < num_epochs:

    if (start == 0):
        cur_perm = np.random.permutation(max_ind)

    # Sample random training images
    stop = start + batch_size
    random_images = x_train[cur_perm[start:stop]]

    # Decode them to reconstructed images
    generated_images = gan.predict(random_images)[0]

    # Combine them with real images
    real_images = x_train[start: stop]
    combined_images = np.concatenate([generated_images, real_images])

    # Assemble labels discriminating real from fake images
    labels = np.concatenate([0.95*np.ones((batch_size, 1)),
                             np.zeros((batch_size, 1))])  # 0=real, 1=fake
    # Add random noise to the labels - important trick!
    labels += 0.05 * np.random.random(labels.shape)

    # Train the discriminator
    d_loss = discriminator.train_on_batch(combined_images, labels)

    # Assemble labels that say "all real images"
    misleading_targets = np.zeros((batch_size, 1))

    # Train the generator (via the AN model,
    # where the discriminator weights are frozen)
    a_loss = gan.train_on_batch(real_images, [real_images,misleading_targets])

    start += batch_size
    if start > len(x_train) - batch_size:
        start = 0

        # Print metrics
        print('discriminator loss at epoch %s: %s' % (epoch, d_loss))
        print('adversarial loss at epoch %s: %s' % (epoch, a_loss))

        adv_loss[epoch,:] = a_loss
        disc_loss[epoch,:] = d_loss

        # Calculate and save the validation loss (mse on image only)
        val_adv_loss[epoch,:] = gan.evaluate(x_test, [x_test, np.ones(x_test.sh
ape[0])])

        epoch += 1
```

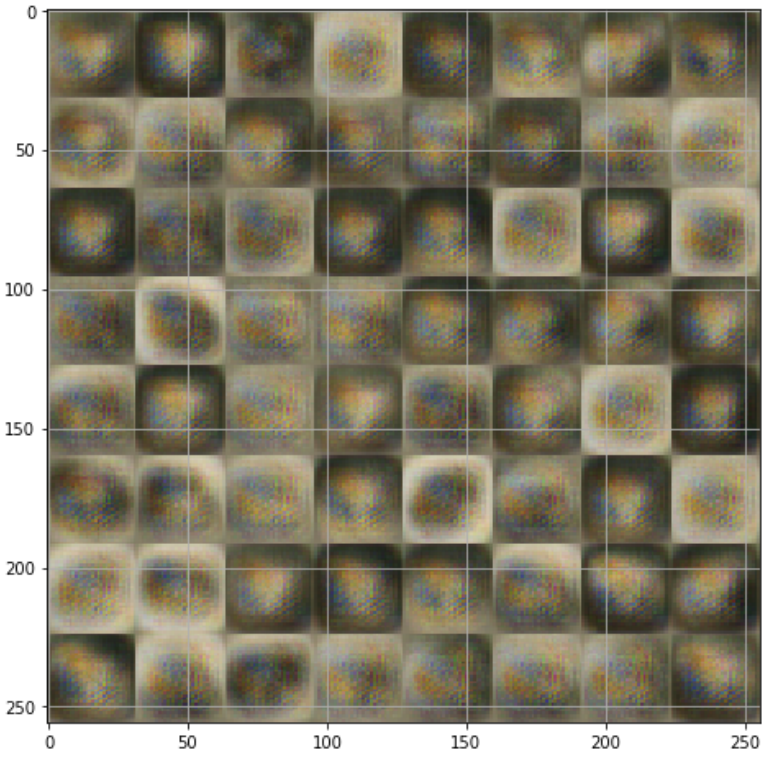
```
Number of epochs = 100
```

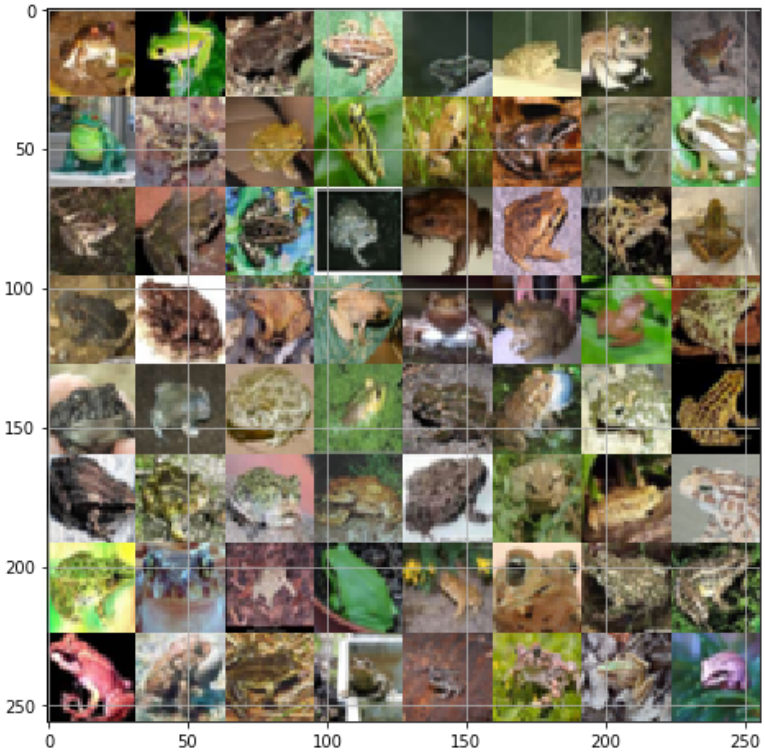
```
/usr/local/lib/python3.6/dist-packages/keras/engine/training.py:490: UserWarnin
g: Discrepancy between trainable weights and collected trainable weights, did y
ou set `model.trainable` without calling `model.compile` after ?
  'Discrepancy between trainable weights and collected trainable'
```

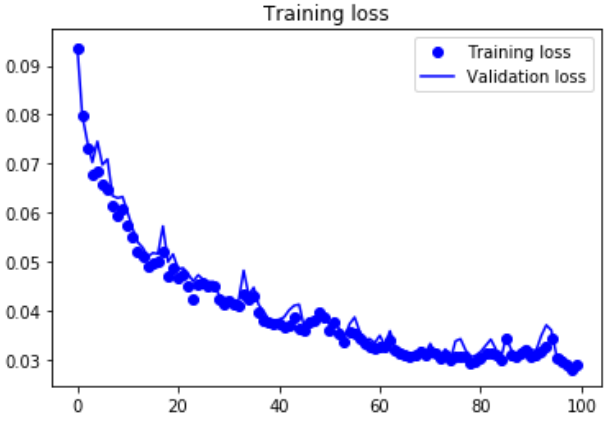
```
discriminator loss at epoch 0: 0.18028562
adversarial loss at epoch 0: [0.18032476, 0.093454756, 0.8687]
1000/1000 [==============================] - 1s 1ms/step
discriminator loss at epoch 1: 0.15551665
adversarial loss at epoch 1: [0.14977415, 0.07991409, 0.69860053]
1000/1000 [==============================] - 0s 172us/step
discriminator loss at epoch 2: 0.34671268
adversarial loss at epoch 2: [0.15738052, 0.07327927, 0.8410126]
1000/1000 [==============================] - 0s 159us/step
discriminator loss at epoch 3: 0.14955622
adversarial loss at epoch 3: [0.18701223, 0.06767388, 1.1933835]
1000/1000 [==============================] - 0s 173us/step
discriminator loss at epoch 4: 0.14134766
adversarial loss at epoch 4: [0.16265929, 0.06852975, 0.9412953]
1000/1000 [==============================] - 0s 156us/step
discriminator loss at epoch 5: 0.13194627
adversarial loss at epoch 5: [0.1432459, 0.065712914, 0.77532995]
1000/1000 [==============================] - 0s 184us/step
discriminator loss at epoch 6: 0.12471356
adversarial loss at epoch 6: [0.14919451, 0.06469269, 0.84501815]
1000/1000 [==============================] - 0s 178us/step
discriminator loss at epoch 7: 0.120787874
adversarial loss at epoch 7: [0.16098368, 0.06153433, 0.99449354]
1000/1000 [==============================] - 0s 181us/step
discriminator loss at epoch 8: 0.12550056
adversarial loss at epoch 8: [0.17431979, 0.05933746, 1.1498233]
1000/1000 [==============================] - 0s 180us/step
discriminator loss at epoch 9: 0.1217459
adversarial loss at epoch 9: [0.16072561, 0.060867567, 0.9985804]
1000/1000 [==============================] - 0s 159us/step
discriminator loss at epoch 10: 0.12457724
adversarial loss at epoch 10: [0.14521411, 0.057543747, 0.8767037]
1000/1000 [==============================] - 0s 174us/step
discriminator loss at epoch 11: 0.12327406
adversarial loss at epoch 11: [0.1332396, 0.055106293, 0.78133297]
1000/1000 [==============================] - 0s 163us/step
discriminator loss at epoch 12: 0.11302555
adversarial loss at epoch 12: [0.14320505, 0.052039113, 0.91165936]
1000/1000 [==============================] - 0s 173us/step
discriminator loss at epoch 13: 0.12041547
adversarial loss at epoch 13: [0.13087624, 0.051115148, 0.7976109]
1000/1000 [==============================] - 0s 162us/step
discriminator loss at epoch 14: 0.12149854
adversarial loss at epoch 14: [0.12838358, 0.049119193, 0.79264385]
1000/1000 [==============================] - 0s 172us/step
discriminator loss at epoch 15: 0.12402106
adversarial loss at epoch 15: [0.13228256, 0.049808905, 0.8247366]
1000/1000 [==============================] - 0s 159us/step
discriminator loss at epoch 16: 0.1258336
adversarial loss at epoch 16: [0.1242679, 0.05014444, 0.74123454]
1000/1000 [==============================] - 0s 173us/step
discriminator loss at epoch 17: 0.13646542
adversarial loss at epoch 17: [0.20735362, 0.05222407, 1.5512955]
1000/1000 [==============================] - 0s 158us/step
discriminator loss at epoch 18: 0.12054384
adversarial loss at epoch 18: [0.12931132, 0.047073223, 0.8223809]
1000/1000 [==============================] - 0s 171us/step
discriminator loss at epoch 19: 0.11518071
adversarial loss at epoch 19: [0.12818187, 0.048768613, 0.7941326]
1000/1000 [==============================] - 0s 160us/step
discriminator loss at epoch 20: 0.11254447
adversarial loss at epoch 20: [0.124004945, 0.046606585, 0.7739836]
1000/1000 [==============================] - 0s 173us/step
```

Display a few reconstructed images and the training plots:

In [0]:
```
ae_images, discrim = gan.predict(x_train[0:64])
show_images(ae_images)
show_images(x_train[0:64])

loss = adv_loss[:,1]  # Set up so this is mse on the images
val_loss = val_adv_loss[:,1]
epochs = range(num_epochs)

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training loss')
plt.legend()

plt.show()
```


0
50
100
150
200
250
0
50
100
150
200
250


0
50
100
150
200
250
0
50
100
150
200
250


Training loss
Training loss
Validation loss
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0
20
40
60
80
100