Introduction to Deep Learning

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October 8, 2020

Slides

- Slides available from (this will redirect to my github repo.):

https://git.io/knu-slides-2019

- Other Resources:
  - Keras documentation: http://keras.io/
  - Tensorflow's guide to Keras: https://www.tensorflow.org/guide/keras
  - Another tutorial presentation: https://uwaterloo.ca/data-science/sites/ca.data-science/fil

Goals

- If you're already a deep learning master, not the talk for you!
- Get up and running quickly with Deep Learning
    - In particular, the goal is to build neural networks you can take home today!
- Therefore, use *Keras* to get up and running quickly
- Outline of the session:
    - Basic Usage of Keras (Iris)
    - Convolutional Neural Net in Keras (MNIST)
    - GANs (using MNIST)
- For this lecture, I recommend using *google colaboratory*
    - Machine learning education and research tool setup by google, all the packages are installed, just need a google account to sign in

`https://colab.research.google.com`

Dependencies

However,
If you want to follow along with a local setup:
With python and pip installed, you can pull the dependencies by pip installing (you might need to add '–user' to the end of the command lines):

```
# Optional, setup a separate virtualenv to keep everything clean
virtualenv ENV
source ENV/bin/activate
# Download dependencies, tensorflow will be the CPU version
pip install matplotlib tensorflow seaborn scikit-learn h5py jupyter
# Then you could start a notebook
jupyter notebook
```

For a GPU tensorflow, usually best to build yourself (out of scope)

- Now, let's setup a new workspace

Google Colab / Jupyter Basic Usage

- https://colab.research.google.com/notebook
- Offers free jupyter-notebook-as-a-service in the cloud
  - Even offers free access to cloud-based GPUs
- Has all the packages we'll need for today pre-installed
- Demo
  - Basic jupyter usage

```
!ls # execute external commands
import os
?os # help at your fingertips
pi = 3.14159 # interpreter persists over cells
pi*2

def area(radius):
    return pi*radius**2

area(1)

# inline plotting
import numpy as np
import matplotlib.pyplot as plt

x = np.linspace(-3.14, 3.14, 100)
y = np.sin(x)
plt.plot(x, y)
plt.show()
```

Keras

- Deep learning framework built by Google engineer François Chollet
- High-level interface built allowing eg Theano or Tensorflow as a backend
  - Has been accepted into mainline Tensorflow, so always accessible there
- Library written in python, user-friendly interface
- Easy to get started building networks
- Highly modular and easily expandable
  - Can drop down into the underlying library when complex/bespoke operations are needed
- Quickly build and train serious models

imports

- Follow along either on the web-based service, or your own machine
- Lets pull in all the imports and definitions we'll need

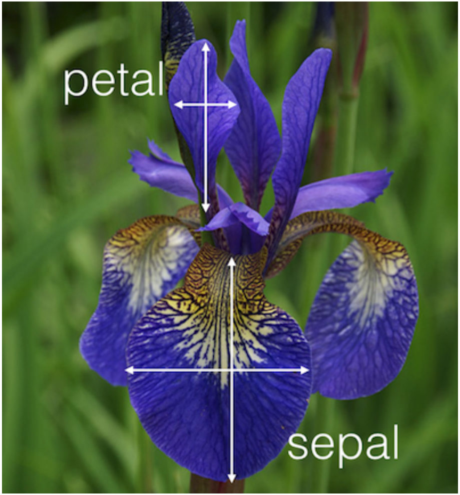
```python
import h5py
import matplotlib
# matplotlib.use("AGG")  # To batch graphics
import matplotlib.pyplot as plt
import os
import seaborn as sns
from sklearn.model_selection import train_test_split
import sklearn
import numpy as np
import tensorflow as tf

keras = tf.keras
Sequential = keras.Sequential
Activation = keras.layers.Activation
Dense = keras.layers.Dense
LeakyReLU = keras.layers.LeakyReLU
BatchNormalization = keras.layers.BatchNormalization
Reshape = keras.layers.Reshape
UpSampling2D = keras.layers.UpSampling2D
Dropout = keras.layers.Dropout
Conv2D = keras.layers.Conv2D
MaxPooling2D = keras.layers.MaxPooling2D
Flatten = keras.layers.Flatten
SGD = keras.optimizers.SGD
mnist = keras.datasets.mnist
```

Overarching Idea of (Supervised) Maching Learning

- Framework for Machine Learning: given a set of data, and set of expected outputs (typically categories), build a system which learns how to connect data to output
- Neural Network is one type, connect stacks of tensor operators with fixed linear and non-linear transformations
- Optimize transformation parameters so as to approximate expected outputs

The iris dataset and a basic network with Keras



- Let's take a concrete example
- The iris dataset is a classic classification task, first studied by Fisher in 1936.
- The goal is, given features measured from a particular iris, classify it into one of three species
  - Iris setosa, virginica, versicolor.
- The variables are: Sepal width and length, petal width and length (all in cm).

Iris dataset

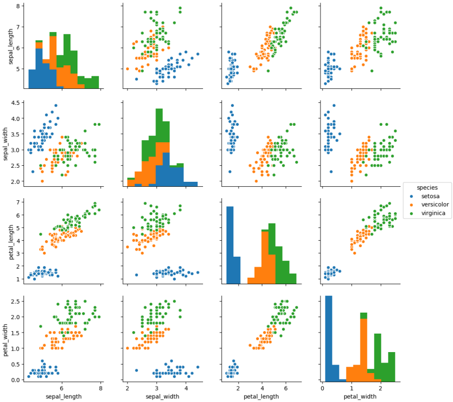
We begin by loading the iris dataset, helpfully available from the seaborn pacakge, which also lets us create plots showing the correlations between the variables.

```
iris = sns.load_dataset("iris")
iris.head()
```

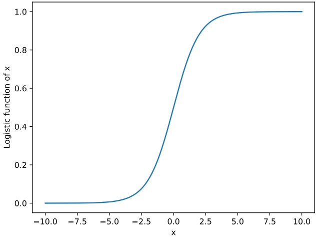
```
   sepal_length  sepal_width  petal_length  petal_width species
0           5.1          3.5           1.4          0.2  setosa
1           4.9          3.0           1.4          0.2  setosa
2           4.7          3.2           1.3          0.2  setosa
3           4.6          3.1           1.5          0.2  setosa
4           5.0          3.6           1.4          0.2  setosa
```

Lets view the basic variables we have. Setosa (blue) looks easily separable by the petal length and width, but versicolor and virginica are a little tricky.

```
plot = sns.pairplot(iris, hue="species")
plot.savefig('iris.png'); 'iris.png'
```

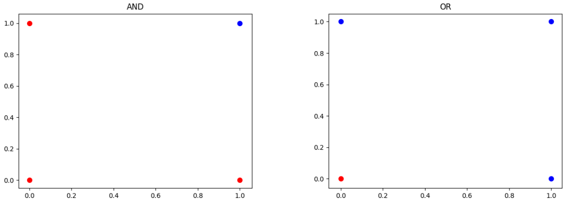


The Logistic Function and Logistic Regression



- The logistic (or sigmoid) function is defined as $f(x) = \frac{1}{1+e^{-x}}$
  - Looks like a classic "turn-on" curve
- Concentrate on the case of two classes (cat/dog or electron/photon), and ask what we want from a classifier output
  - We need to distinguish between the two classes using the output:
  - If the value is 0, it represents the classifier identifying one class (cat)
  - If its near 1, the classifier is identifies the other class (dog)
  - Thus, we need to transform the input variables into 1D, then pass through the logistic function
- This is a simple classification technique called *logistic regression*

Some very simple examples for simple logistic regression



- Let's think about approximating some simple binary functions
- OR and AND gates
  - OR is 0 (red) if both input are 0, 1 (blue) otherwise
  - AND is 1 if both inputs are 1, 0 otherwise
- Can we find logistic function approximations for this?
  - That is, $f(x_1, x_2)$ returns approximately 1 or 0 at the indicated points

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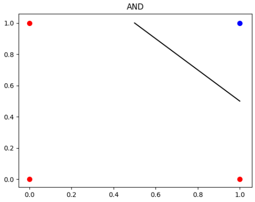

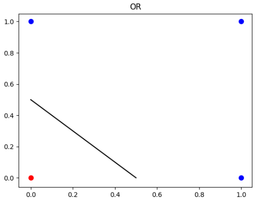

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- Yes! Take the projection perpendicular to the line

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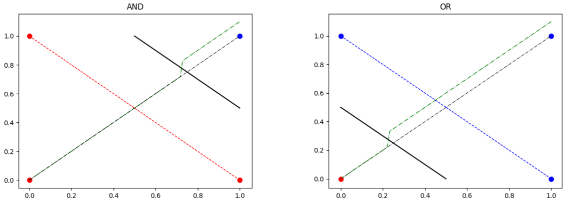

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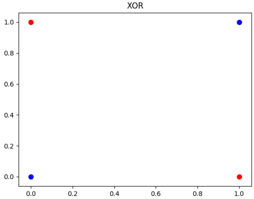
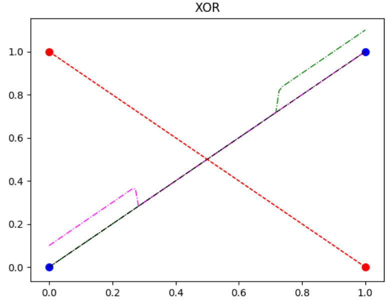
- OR and AND gates
  - OR is 0 (red) if both input are 0, 1 (blue) otherwise
  - AND is 1 if both inputs are 1, 0 otherwise
- Can we find logistic function approximations for this?
  - That is, $f(x_1, x_2)$ returns approximately 1 or 0 at the indicated points
- Yes! Take the projection perpendicular to the line
- and have the logistic turn on at the line (in the 2D plane the logistic function will turn on as a "wave-front" along the black line shown)
  - e.g. $f(x_1, x_2) = \sigma(2x_1 + 2x_2 - 1)$ for OR, $f(x_1, x_2) = \sigma(2x_1 + 2x_2 - 3)$ for AND [σ is our logistic function]

Very simple example with issues for Logistic Regression



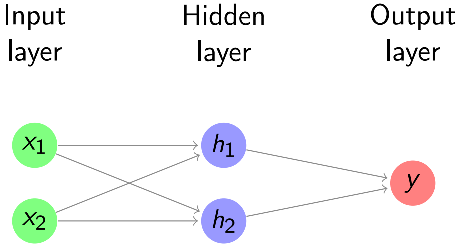
- Now consider the XOR gate: 1 if both inputs are the same, 0 otherwise
- The XOR gate can't be generated with a logistic function!
- Try it: no matter what line you draw, can't draw a logistic function that turns on only the blue!

How to Fix: more logistic curves!



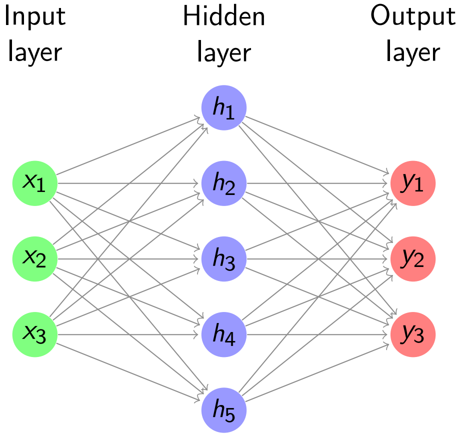
- Can fix by having 2 turn-on curves, one turning on either of the blue points, then summing the result
- $f(x_1, x_2) = \sigma(2x_1 + 2x_2 - 1) + \sigma(-2x_1 - 2x_2 + 1)$

The Feed-Forward Neural Network



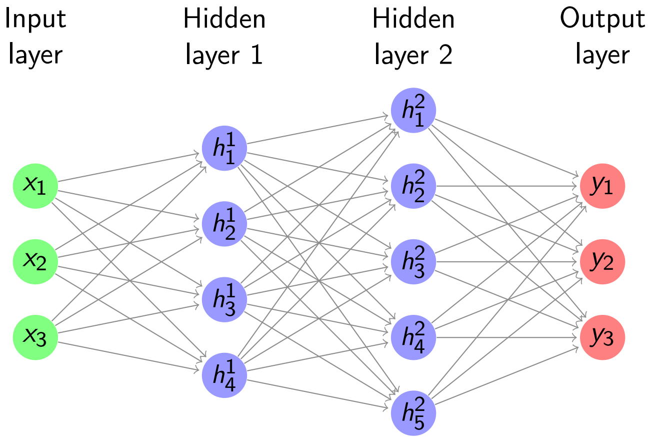
- Consider the structure of what we just made
  - $y = f(x_1, x_2) = \sigma(-1 + 2x_1 + 2x_2) + \sigma(1 - 2x_1 - 2x_2)$
- Decompose the function into:
  - the *input layer* of $\hat{x}$,
  - the *hidden layer* which calculates $h_i = \beta_i \cdot x$ then passes if through the *activation function* σ, (called "sigmoid" in NN terms)
    - There is an extra β_0, called the *bias*, which controls how big the input into the node must be to activate; σ is implicit in the diagram
  - the *output layer* which sums the results of the hidden layer and gives y
    - $y = 0 + 1 \cdot \sigma(h_1) + 1 \cdot \sigma(h_2)$

Feed-Forward Neural Network



- In general, we could have several input variables, and output variables
- In the case of classification, we would usually have a final *softmax* applied to $\hat{y}$, but could use any *activation* φ here also
  - *softmax* normalizes the output layer so it sums to 1: $f_k(x) = \frac{e^{-y_k}}{\sum_i e^{-y_i}}$

Feed-Forward Neural Network



- We can even have several hidden layers
  - The previous layer acts the same as an *input layer* to the next layer
- We call each node in the network a *neuron*
- The deep learning algorithms we will see later are just variations on this theme, using more complicated transformations

Universal Approximation Thereom

Let $\varphi : \mathbb{R} \to \mathbb{R}$ be a nonconstant, bounded, and continuous function. Let I_m denote the m-dimensional unit hypercube $[0,1]^m$. The space of real-valued continuous functions on I_m is denoted by $C(I_m)$. Then, given any $\varepsilon > 0$ and any function $f \in C(I_m)$, there exist an integer N, real constants $v_i, b_i \in \mathbb{R}$ and real vectors $w_i \in \mathbb{R}^m$ for $i = 1, \ldots, N$ such that we may define:

$$F(x) = \sum_{i=1}^{N} v_i \varphi\left(w_i^T x + b_i\right)$$

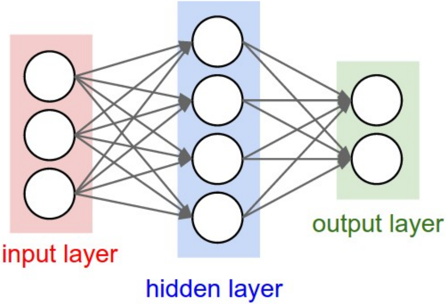
as an approximate realization of the function f; that is,

$$|F(x) - f(x)| < \varepsilon$$

for all $x \in I_m$. In other words, functions of the form $F(x)$ are dense in $C(I_m)$. This still holds when replacing I_m with any compact subset of $\mathbb{R}^m$.

- In brief: with a hidden layer (of enough nodes), any (sensible) function $f : \mathbb{R}^m \to \mathbb{R}$ can be approximated by a feed-forward NN
  - Any (sensible) activation φ can work, not just σ
- There is a simple, graphical proof for those who are interested: http://neuralnetworksanddeeplearning.com/chap4.html

Neural Networks Overview



- Example shown: input vector $\vec{x}$, goes through $\vec{y}_{hidden} = W\vec{x} + \vec{b}$, then $\vec{y}_{output} = \sigma(\vec{y}_{hidden})$ (σ is some non-linear turn-on curve)
- I.e. hidden layer combines $\vec{x}$ by some weights, then if the weighted sum passes a threshold $\vec{b}$, we turn on the output (with the $\sigma(x) = 1/(1 + e^{-x})$ to gate the ops)
- Need to **train** the weight matrix W and the bias vector b and optimize a "loss" function that represents a distance from the target output

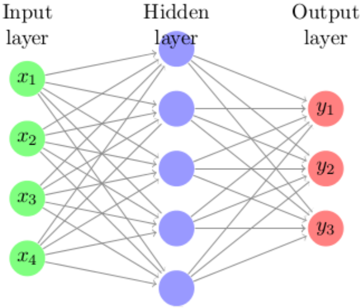
Backpropagation

- The algorithm to train neural networks is called **backpropagation**
- Its essentially a gradient descent implemented taking the network structure into account to speed up evaluation of the partials
- To apply gradient descent, need a function of a single variable, called the *loss*
  - $L(x_i|\sigma) = \sum_i |f(x_i|\sigma) - y_i|^2$ for inputs x_i and known output y_i
- We start with the parameters set to arbitrary values, usually picked from e.g. unit gaussian
- We run a forward pass through the network and calculate the loss
- Using the chain rule, calculate *all* the derivates backward from the loss to the higher layers
- Propagate changes based on the gradient $\Delta w_i = -\eta \frac{\partial f}{\partial w_i}$
- For more on how backpropagation works: http://neuralnetworksanddeeplearning.com/chap2.html

Keras Networks

In order to classify the irises, we'll build a simple network in Keras.

- The basic network type in Keras is the `Sequential` model.
- The `Sequential` model builds a neural network by stacking layers
  - Keras also has a `Graph` model that allows arbitrary connections
- It builds up like lego, adding one layer on top of another and connecting between the layers
  - Keras comes with a menagerie of pre-built layers for you to use.
- Interface to/from the model with numpy arrays



Model

- Our model will be a simple NN with a single hidden layer
- We start by building a Sequential model and add a Dense (fully-connected) layer, with sigmoid activation
- Dense: standard layer, all inputs connect to all outputs: $\hat{y} = W\hat{x} + \hat{b}$
    - `keras.layers.Dense(output_dim)`
    - Can also set the initalization, add an activation layer inline, add regularizers inline, etc.
- Activation: essentially acts as a switch for a given node, turns output on/off based on threshold
    - `keras.layers.Activation(` *type* `)`
        - Where *type* might be:
    - *sigmoid*: $f(x) = \frac{1}{1+e^{-x}}$
    - *tanh*: $f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
    - *relu*: $f(x) = \max(0, x)$, 'rectified linear unit'
    - *softplus*: $f(x) = \ln(1 + e^x)$, smooth approx. to *relu*
    - *softmax*: $f_k(x) = \frac{e^{-x_k}}{\sum_i e^{-x_i}}$ for the k'th output, as last layer of categorical distribution, represents a probability distribution over the outputs

Build a model: Python code

```python
# Build a model
model = Sequential()

model.add(Dense(128, input_shape=(4,)))
model.add(Activation('sigmoid'))
# model.add(Dense(128))
# model.add(Activation('sigmoid'))
model.add(Dense(3))
model.add(Activation('softmax'))

model.compile(optimizer='adam', loss='categorical_crossentropy',
              metrics=['accuracy'])
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 128)               640
_________________________________________________________________
activation_1 (Activation)    (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 387
_________________________________________________________________
activation_2 (Activation)    (None, 3)                 0
=================================================================
Total params: 1,027
Trainable params: 1,027
```

More on model building

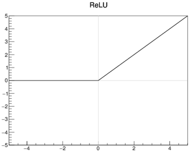
- When `add`'ing layers, keras takes care of input/output size details
  - Except for the input layer, which must be specified
  - We explicitly gave the network `(4,)` for our 4 input variables
- The final layer we make size 3 after a softmax activiation
  - This will output the network probability for each of the potential iris classes as a numpy array `(nsamples, (` $p_{setosa}, p_{virginica}, p_{versicolor}$ `))`
- We `compile` the model with an optimizer and loss function
  - The loss function will be minimized during the training phase
- We can give auxilliary `metrics` which will be calculated with the loss
- Keras automatically takes care of calculating derivatives through the network for the backprop phase
- We could be more explicit in creating the functions if we want more control over hyperparameters:

```
model.compile(loss=keras.losses.mean_squared_error,
              optimizer=keras.optimizers.SGD(lr=0.0005, momentum=0.9,
                                             nesterov=True))
```

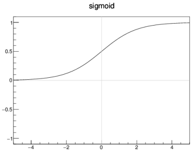
Here we used the adam optimizer which automatically updates the step sizes used for parameter optimization, with a categorical cross-entropy loss, which measures $-\sum_i t_i \log p_i$ where t_i is 1 for the true label and p_i is the probability of the ith label assigned by the model. As the model assigns higher probability to the correct label, the cross-entropy goes to 0.

- Other options to consider:
  - Activation: *sigmoid*, *softmax*, *linear*, *tanh*, *relu*, ...
  - Optimizer: *SGD*, *RMSprop*, *Adagrad*, *Adadelta*, *Adam*, ...
  - Loss: *categorical_crossentropy*, *binary_crossentropy*, *mean_squared_error*, ...

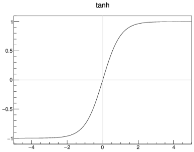
ReLU



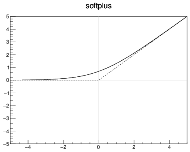
sigmoid



tanh



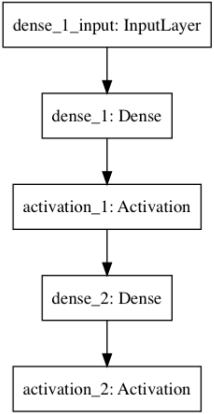
softplus



Model picture

If pydot is installed we can also output a picture of the network

```
keras.utils.plot_model(model, to_file='iris_model.png')
```



Training Code

```
# Split the variables to train, and the target
variables = iris.values[:, :4]
species = iris.values[:, 4]

# One hot encode the species target
smap = {'setosa' : 0, 'versicolor' : 1, 'virginica' : 2}
species_enc = np.eye(3)[list(smap[s] for s in species)]

# To show we are simply passing numpy arrays of the data
print(variables[0], species[0], species_enc[0])

train_X, test_X, train_y, test_y = \
  train_test_split(variables, species_enc, train_size=0.8, random_state=0)
model.fit(train_X, train_y, epochs=15, batch_size=1, verbose=1)
```

```
[5.1 3.5 1.4 0.2] setosa [ 1.  0.  0.]
Epoch 1/15
120/120 [==============================] - 0s - loss: 0.2873 - acc: 0.9500

...

Epoch 15/15
120/120 [==============================] - 0s - loss: 0.1477 - acc: 0.9583
```

Training

- Now we fit to the training data.
- We can set the number of `epochs`, `batch_size`, and `verbose`'ity
  - Epochs: number of training passes through the complete dataset
  - Batch size: number of datapoints to consider together when updating the network
- We pass through the input data as a numpy array (nsamples, 4)
- We pass the output as (nsamples, 3) where for each sample one of the positions is 1, corresponding to the correct class.
- We use the `np.eye` identity matrix creator to help us transform the raw species information (which labels classes setosa, virginica, versicolor) to the expected format
  - Setosa = `(1, 0, 0)`
  - Versicolor = `(0, 1, 0)`
  - Virginica = `(0, 0, 1)`
- We fit the model to a labelled dataset simply by calling `fit` with the dataset `train_X` and the true labels `train_y`

Evaluation

- After running the model, we can `evaluate` how well it works on the labelled *test* data we kept aside for *overfitting* evaluation purposes.
  - Overfitting is when the model fits to the training set in a way that doesn't generalize to unseen samples
  - One usually also has a separate *validation* set, use the *test* set on a single model, choose a model you like, then check the *hyperparameters* didn't cause bias by checking the *validation*

```python
# The evaluation passes out the overall loss,
# as well as any other metrics you included
# when compiling the model
loss, accuracy = model.evaluate(test_X, test_y, verbose=0)
print("Loss={:.2f}\nAccuracy = {:.2f}".format(loss, accuracy))
```

```
Loss=0.11
Accuracy = 0.97
```

Prediction

- And we can ask the model to `predict` some unlabelled data
  - For illustration, we just use our test data, and compare the true label against the 'prediction'
  - In the output, I stack the true answers (first rows), and the prediction, which can basically be interpreted as the model's probability for each category (second rows)

```python
pred_y = model.predict(test_X)
print(np.stack([test_y, pred_y], axis=1)[:10])
```

```
[[[  0.00000000e+00   0.00000000e+00   1.00000000e+00]
  [  2.63856982e-05   8.96630138e-02   9.10310626e-01]]

 [[  0.00000000e+00   1.00000000e+00   0.00000000e+00]
  [  1.57812089e-02   9.63519156e-01   2.06995625e-02]]

 [[  1.00000000e+00   0.00000000e+00   0.00000000e+00]
  [  9.96497989e-01   3.50204227e-03   1.25929889e-09]]

 [[  0.00000000e+00   0.00000000e+00   1.00000000e+00]
  [  4.74178378e-05   1.32592529e-01   8.67359996e-01]]

 [[  1.00000000e+00   0.00000000e+00   0.00000000e+00]
```

MNIST digit recognition and Convolutional Networks

- Another, more recent, classic classification task.
- Given a 28x28 image of a handwritten digit, can you train a classifier to recognize the numbers from 0 to 9?
- Keras has the ability to download the dataset and parse it into numpy arrays. We use `to_categorical` to one hot encode the true labels (which number did they write?) as for the irises

```
(x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()
```

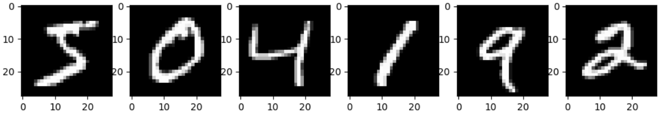
```
from keras.utils.np_utils import to_categorical
# or to_categorical = tf.keras.utils.np_utils.to_categorical

print(y_train[:4])
y_train_enc = np.eye(10)[y_train]
y_test_enc = to_categorical(y_test) # many ways to do the same thing
print(y_train_enc[:4])
```

```
[5 0 4 1]
[[ 0.  0.  0.  0.  0.  1.  0.  0.  0.  0.]
 [ 1.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
 [ 0.  0.  0.  0.  1.  0.  0.  0.  0.  0.]
 [ 0.  1.  0.  0.  0.  0.  0.  0.  0.  0.]]
```

Examples

- We can use `matplotlib.pyplot` to show a few example digits
- In *jupyter*, matplotlib results will show automatically, so you don't need to print it out (or resize it for that matter)

```
print(x_train.shape, y_train_enc.shape)
plt.clf()
for i in range(6):
    plt.subplot(1,6,i+1)
    plt.imshow(x_train[i], cmap='gray')

F = plt.gcf(); F.set_size_inches((14,2))
plt.savefig('mnist-examples.png');
```



Simple Network

- We can start by simply trying a basic neural network as before.
- ‘Flatten‘ takes the 2D input and concatenates the rows together to a 1D form suitable for passing to a ‘Dense‘ layer.

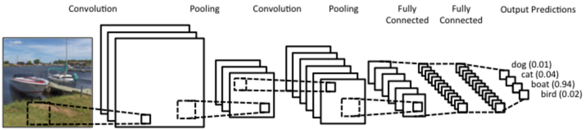
```
model = Sequential()
model.add(Flatten(input_shape=(28,28)))
model.add(Dense(128))
model.add(Activation('sigmoid'))
model.add(Dense(128))
model.add(Activation('sigmoid'))
model.add(Dense(10))
model.add(Activation('softmax'))

model.compile(optimizer='adam', loss='categorical_crossentropy',
              metrics=['accuracy'])
```

- And `fit` and `evaluate` as we did before

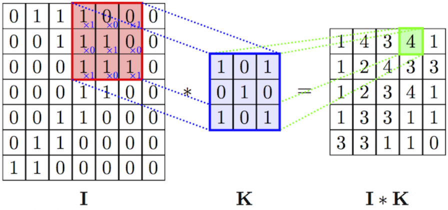
```
model.fit(x_train, y_train_enc, epochs=3, verbose=1)
loss, accuracy = model.evaluate(x_test, y_test_enc, verbose=0)
print("Loss={:.2f}\nAccuracy = {:.2f}".format(loss, accuracy))
```

```
Epoch 1/3
60000/60000 [==============================] - 4s - loss: 0.5373 - acc: 0.8
Epoch 2/3
60000/60000 [==============================] - 4s - loss: 0.3729 - acc: 0.8
Epoch 3/3
60000/60000 [==============================] - 4s - loss: 0.3207 - acc: 0.9
Loss=0.30
Accuracy = 0.91
```

A Convolutional Network



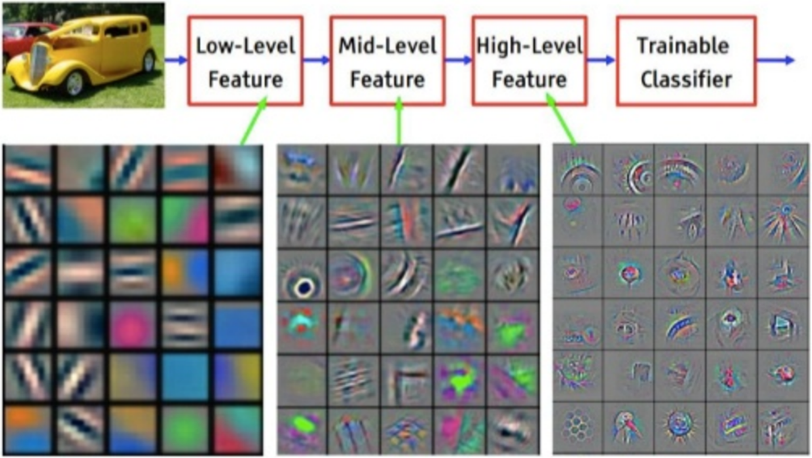
- One of the great advances in image classification in recent times
- We have some filter kernel K of size $n \times m$ which we apply to every $n \times m$ cell on the original image to create a new filtered image.
- It has been seen that applying these in multiple layers of a network can build up multiple levels of abstraction to classify higher-level features.
    - And, importantly, is trainable many, many layers deep



Reference: `http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/`

What is the Network Learning?

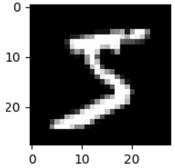
- In general a difficult question to answer
- Here, Zeiler and Fergus (2013) took a trained network and *optimized the input* to activate particular nodes to give an idea
  - Start with noise, then GD on the input, optimizing the node activation



Reshaping data for Keras

- Convolution of this type in Keras is provided by the `Conv2D` layer
- `Conv2D` requires passing an array of *width x height x channels*
  - Where channels might represent colors of an image
- We have black and white images so we'll just reshape it into the required form with a single channel.
- We plot the image just check show the shaping is correct

```
x_train_dense = x_train.reshape((len(x_train), 28,28,1))
x_test_dense = x_test.reshape((len(x_test), 28,28,1))

plt.clf()
plt.imshow(x_train_dense[0,:,:,0], cmap="gray")
F = plt.gcf(); F.set_size_inches((2,2)); plt.savefig("testimg.png");
```



Building a Convolutional Neural Network in Keras

- Now, lets build a convolutional neural network!
- Generally, `Conv2D` will be stacked on top of each other with `MaxPooling2D` layers and learn edge detection at lower layers and higher level feature extraction in subsequent layers.
- But just to show how to use them in keras, we'll just create one convolution layer with 32 filters, then `Flatten` it into a 1D array and pass it into a `Dense` hidden layer before the output.
- We can set the `kernel_size` (m x n size of the filter), and the number of filters used

Building a Convolutional Neural Network in Keras

- We can set the `kernel_size` ($m \times n$ size of the filter), and the number of filters used

```
model = Sequential()

model.add(Conv2D(32, kernel_size=(3,3),input_shape=(28,28,1)))
model.add(Activation('relu'))
model.add(Flatten())
model.add(Dense(128))
model.add(Activation('sigmoid'))
model.add(Dense(10))
model.add(Activation('softmax'))

model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Training

And train the model. This is already starting to get to the point where a GPU would be extremely helpful!

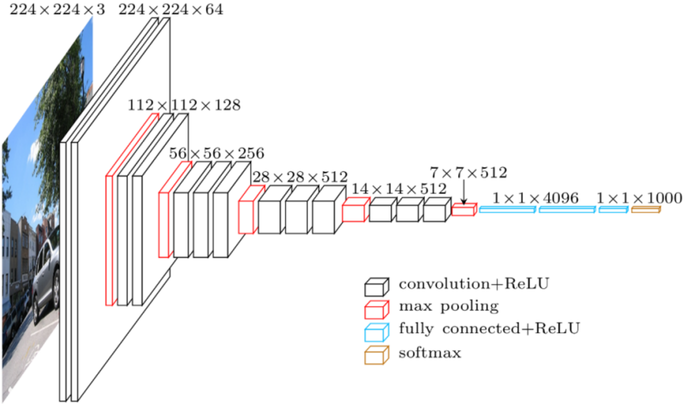
```
model.fit(x_train_dense, y_train_enc, epochs=4, verbose=1)
```

```
Epoch 1/4
60000/60000 [==============================] - 65s - loss: 0.4544 - acc: 0.
Epoch 2/4
60000/60000 [==============================] - 70s - loss: 0.1745 - acc: 0.
Epoch 3/4
60000/60000 [==============================] - 68s - loss: 0.1369 - acc: 0.
Epoch 4/4
60000/60000 [==============================] - 69s - loss: 0.1227 - acc: 0.
<keras.callbacks.History object at 0x11d742390>
```

```
loss, accuracy = model.evaluate(x_test_dense, y_test_enc, verbose=0
print("Loss={:.3f}\nAccuracy = {:.3f}".format(loss, accuracy))
```

```
Loss=0.117
Accuracy = 0.964
```

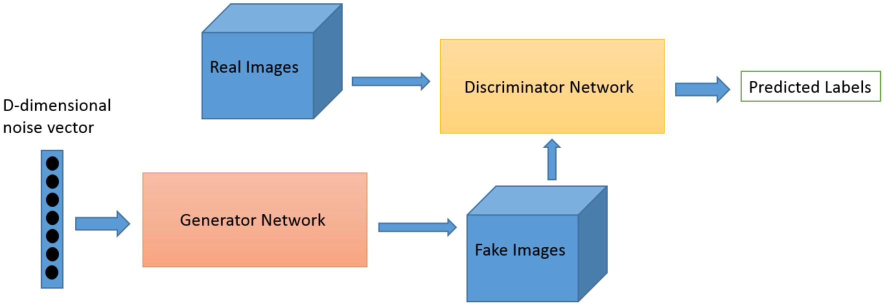
Realistic Networks



- Example of a real network used for image classification, VGG-16
- Typically, networks consist of several convolution layers following by max pooling layers (take the max from a 2x2 square)

A Convolution GAN

- The idea is to train two adverserial networks,
  - One is trying to create images equivalent to the MNIST dataset
    - Given an input of noise, the *latent space*
  - The other trying to label the images as either from the dataset or fake
    - Fake = generated by the opposing dataset



- References:
  - For more on GANs and their uses: `https://arxiv.org/pdf/1701.00160.pdf`
  - Code based on: `https://github.com/jacobgil/keras-dcgan`
  - Some tricks for training GANs `https://github.com/soumith/ganhacks`

Idea: Image generator network

- We start with the image generation network
- Essentially a image classifier in reverse.
- The top layer is for high-level feature inputs which we'll randomly set during the training.
- We then pass through Dense layers and then reshape into a *7 x 7 x channels* image-style layer.
- We `Upsampling2D` and pass through convolutional filters until the last layer which outputs a *28x28x1* image as expected of an MNIST greyscale image.
    - Essentially we're *adding* features as we go up, instead of *extracting* features as we go down
- `BatchNormalization` is a technique to improve the network stability by providing the next layer inputs with zero mean and unit variance

Generator

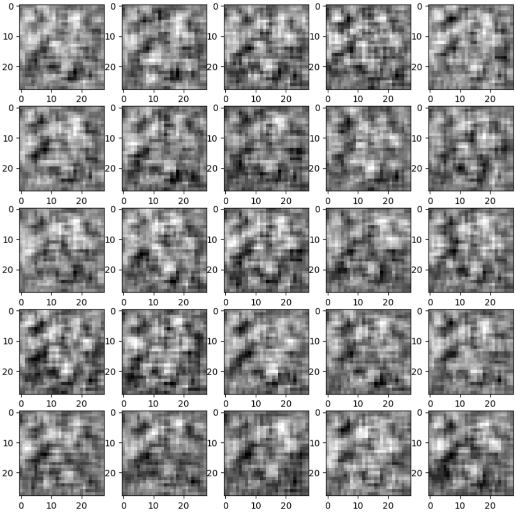
```
# Complete code for the generator model
nfeatures = 100

generate = Sequential()
generate.add(Dense(1024, input_dim=nfeatures))
generate.add(Activation('tanh'))
generate.add(Dense(128*7*7))
generate.add(BatchNormalization())
generate.add(Activation('tanh'))
generate.add(Reshape((7, 7, 128)))
generate.add(UpSampling2D(size=(2,2)))
generate.add(Conv2D(64, (5,5), padding='same'))
generate.add(Activation('tanh'))
generate.add(UpSampling2D(size=(2,2)))
generate.add(Conv2D(1, (5, 5), padding='same'))
generate.add(Activation('sigmoid'))
generate.compile(loss="binary_crossentropy", optimizer="SGD")
```

Generator Test

Now, just to check everythings put together properly, randomly pass some data through the network and check we get image outputs as expected.

```
nim = 25
pred = generate.predict(np.random.uniform(0, 1, (nim,nfeatures)))

plt.clf()
for i in range(nim):
    plt.subplot(np.sqrt(nim),np.sqrt(nim),i+1)
    plt.imshow(pred[i,:,:,0], cmap='gray')

pred[0].shape, np.average(pred[0])
F = plt.gcf(); F.set_size_inches((10,10))
plt.savefig("genimg_no.png")
```

Example images, pre-training



Discriminator

- Next, we create the discriminating network, with an image input
- As for classification, we have a convolutional layer attached to Dense layers.
- For the output, we now have a single sigmoid with interpretation:
  - 0: The network thinks its definitely a generated image
  - 1: The network thinks its definitely a real MNIST dataset image

Discriminator

```
# Complete code for the discriminator network
discr = Sequential()
discr.add(Conv2D(64, (5,5), input_shape=(28,28,1), padding='same'))
discr.add(Activation('tanh'))
discr.add(MaxPooling2D((2,2)))
discr.add(Conv2D(128, (5,5)))
discr.add(Activation('tanh'))
discr.add(MaxPooling2D((2,2)))
discr.add(Dropout(0.5))
discr.add(Flatten())
discr.add(Dense(1024))
discr.add(Activation('tanh'))
discr.add(Dense(1))
discr.add(Activation('sigmoid'))
discr.compile(loss='binary_crossentropy',
              optimizer=SGD(lr=0.0005, momentum=0.9,
                            nesterov=True))
```

Test the discriminator

- Test the network with a few MNIST images and some random images.
- Since the network isn't trained we don't yet expect any differences in the output.

```
x_prepred = np.concatenate(
    [x_train[:5,:,:].reshape(5,28,28,1) / 256.,
     np.random.uniform(0, 1, (5, 28, 28, 1))], axis=0)
discr.predict(x_prepred)
```

0.53229088 0.53476292 0.53820759 0.5288614 0.52571678 0.57405

GAN

- Now we set up a network which will be used to train the generation network.
- Keras allows us to simply add the models we just created together into a Sequential like they were ordinary layers.
- So, we feed the generator output into the discriminator input and set up an optimizer which will try to drive the generator to produce MNIST-like images (i.e. to fool the discriminator).
- Keras allows us to turn layer training on and off through the "trainable" variable attached to a layer, so when we train the generator we can easily turn training for the discriminator off.

Setup GAN

- Using Keras, we can simply add the generator and discriminator sub-networks into a new, combined network, similarly to any other layer!
- We can also simply tell it to turn off training the discriminator weights when we are optimizing the generator!

```
gen_discr = Sequential()
gen_discr.add(generate)
discr.trainable = False
gen_discr.add(discr)
gen_discr.compile(loss='binary_crossentropy',
                  optimizer=SGD(lr=0.0005, momentum=0.9,
                                nesterov=True),
                  metrics=['accuracy'])
discr.trainable = True
```

Training the GAN

- Finally, we have the actual training
- Here, we setup the batches ourselves and alternate between training the discriminator and generator
  - `model.train_on_batch`
  - This was previously put together by Keras itself
- We start by taking a batch of MNIST images (labeled 1), and generator images (labeled 0) and run a training batch on the discriminator network
- Then, we turn off training off the discriminator and run training on the generator+discriminator network with random high-level feature inputs to the generator
- We try to drive all the outputs to 1, i.e. train the generator to more MNIST-like images (as according to the discriminator network)
- Last remark: we are saving the networks after each epoch with `model.save`
  - Load with `keras.models.load_model`

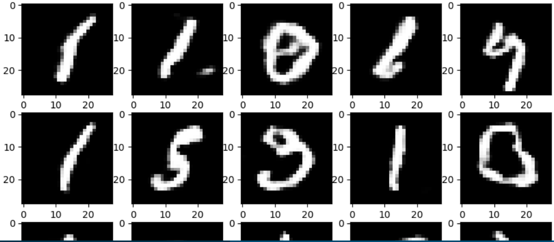
Training the GAN

```
batch_size = 100
n_epochs = 10
print_every_nth_epoch = 50
x_tru_all = x_train.reshape(len(x_train), 28, 28, 1) / 256.

zeros = np.array([0]*batch_size)
ones = np.array([1]*batch_size)
oneszeros = np.array([1]*batch_size + [0]*batch_size)

losses_d = []
losses_g = []
for epoch in range(n_epochs):
    print ("Epoch", epoch)
    discr.save("/discr-"+str(epoch))
    generate.save("/generate-"+str(epoch))
    for i in range(0, len(x_train), batch_size):
        x_gen = generate.predict(np.random.uniform(0, 1, (batch_size, nfeatures)))
        x_tru = x_tru_all[i:i+batch_size]
        # Train the discriminator by taking example MNIST and generator-produced images
        discr.trainable=True
        loss_d = discr.train_on_batch(np.concatenate([x_tru, x_gen], axis=0), oneszeros)
        # Now, turn discriminator training off, so we can train the generator
        discr.trainable=False
        loss_g = gen_discr.train_on_batch(np.random.uniform(0, 1, (batch_size, nfeatures)), ones)
        if i % (print_every_nth_epoch*batch_size) == 0:
            print (i / batch_size, "discr", loss_d, "--", "gen", loss_g[0], "( acc.", loss_g[1], ")")
        losses_g.append(loss_g)
        losses_d.append(loss_d)
```

Checking results

- Lets see how we did, lets just generate a bunch of images

```
nim = 25
pred = generate.predict(np.random.uniform(0, 1, (nim,nfeatures)))

plt.clf()
for i in range(nim):
    plt.subplot(np.sqrt(nim),np.sqrt(nim),i+1)
    plt.imshow(pred[i,:,:,0], cmap='gray')

pred[0].shape, np.average(pred[0])
F = plt.gcf(); F.set_size_inches((10,10)); plt.savefig("genimg_after.png"); "genimg
```

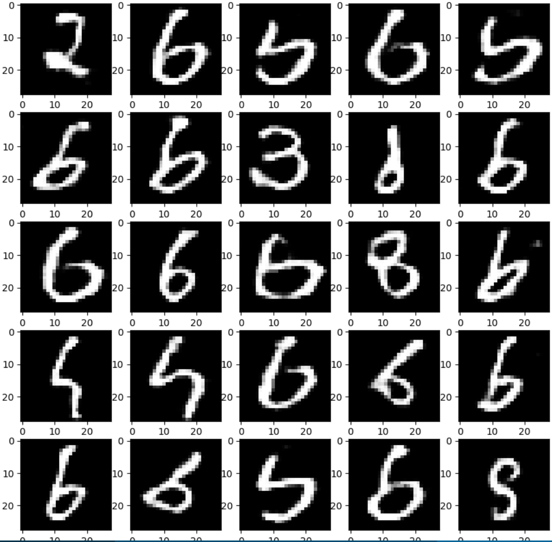


Good images

- Whats the "best" being produced by the GAN?
- Only accept above 0.9 from discriminator

```
nim = 25
target = .9

plt.clf()
for i in range(nim):
    best = 0; pred=None
    while best < target:
        pred = generate.predict(np.random.uniform(0, 1, (1,nfeatures)))
        best = discr.predict(pred)[0][0]
    plt.subplot(np.sqrt(nim),np.sqrt(nim),i+1)
    plt.imshow(pred[0,:,:,0], cmap='gray')

pred[0].shape, np.average(pred[0])
F = plt.gcf(); F.set_size_inches((10,10)); plt.savefig("genimg40_best.9.png"); "genimg40_best.9.png"
```

Good Images

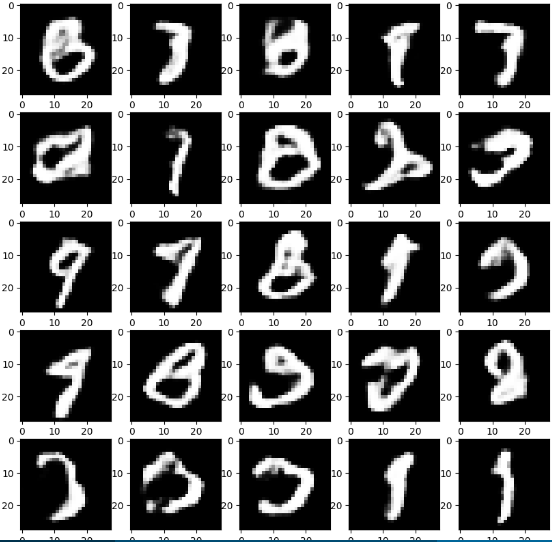


Bad images

- Whats the "worst" being produced by the GAN?
- Only accept below 0.1 from discriminator

```
nim = 25
target = .1

plt.clf()
for i in range(nim):
    best = 1; pred=None
    while best > target:
        pred = generate.predict(np.random.uniform(0, 1, (1,nfeatures)))
        best = discr.predict(pred)[0][0]
    plt.subplot(np.sqrt(nim),np.sqrt(nim),i+1)
    plt.imshow(pred[0,:,:,0], cmap='gray')

pred[0].shape, np.average(pred[0])
F = plt.gcf(); F.set_size_inches((10,10)); plt.savefig("genimg40_worst.1.png"); "genimg40_worst.1.png"
```

Bad images



Extensions

- Try different networks, what works well, what fails badly?
- Add another set of inputs hot-one encoding the number you want to generate,
    - The discriminator will need to say which number it believes its seeing as well as how likely it is to be real
    - The generator will need to train with the number output as a loss also
- Some further ideas on the next pages, work in progress code :-)

Train requiring GAN to also output the correct number

```
nfeatures = 100

generate = Sequential()
generate.add(Dense(1024, input_dim=(nfeatures + 10)))
generate.add(Activation('tanh'))
generate.add(Dense(128*7*7))
generate.add(BatchNormalization())
generate.add(Activation('tanh'))
generate.add(Reshape((7, 7, 128)))
generate.add(UpSampling2D(size=(2,2)))
generate.add(Conv2D(64, (5,5), padding='same'))
generate.add(Activation('tanh'))
generate.add(UpSampling2D(size=(2,2)))
generate.add(Conv2D(1, (5, 5), padding='same'))
generate.add(Activation('sigmoid'))
generate.compile(loss="binary_crossentropy", optimizer="SGD")
```

Create the Discriminator

```
discr = Sequential()
discr.add(Conv2D(128, (5,5), input_shape=(28,28,1), padding='same'))
discr.add(Activation('relu'))
discr.add(MaxPooling2D((2,2)))
discr.add(Conv2D(256, (5,5)))
discr.add(Activation('relu'))
discr.add(MaxPooling2D((2,2)))
discr.add(Dropout(0.5))
discr.add(Flatten())
discr.add(Dense(1024))
discr.add(Activation('tanh'))
discr.add(Dense(11))  # 1 for real or fake, then 10 for which number
discr.add(Activation('sigmoid'))
discr.compile(loss='categorical_crossentropy', optimizer=SGD(lr=0.0005, momentum=0.9, nesterov=True),
              metrics=['accuracy'])
```

Create the combined network

```
gen_discr = Sequential()
gen_discr.add(generate)
discr.trainable = False
gen_discr.add(discr)
gen_discr.compile(loss='categorical_crossentropy', optimizer=SGD(lr=0.0005, momentum=0.9, nesterov=True),
                  # optimizer='adam',
                  metrics=['accuracy'])
discr.trainable = True

batch_size = 100
n_epochs = 50
print_every_nth_epoch = 50
x_tru_all = x_train.reshape(len(x_train), 28, 28, 1) / 256.

zeros = np.array([0]*batch_size)
ones = np.array([1]*batch_size)
oneszeros = np.array([1]*batch_size + [0]*batch_size)
```

Pre-train the discriminator on the (untrained) generator output and real MNIST

```
# pre train the gan to be able to distinguish numbers
pre_losses_d = []
for epoch in range(5):
    print ("Epoch", epoch)
    for i in range(0, len(x_train), batch_size):
        one_hot_gen = np.eye(10)[np.random.random_integers(0, 9, size=(batch_size,))]
        x_inp = np.concatenate([np.random.uniform(0, 1, (batch_size, nfeatures)), one_hot_gen], axis=1)
        x_gen = generate.predict(x_inp)
        x_tru = x_tru_all[i:i+batch_size]
        y_tru = y_train_enc[i:i+batch_size]
        discr.trainable = True
        for_d_tru = np.concatenate([np.zeros((batch_size,1)), y_tru], axis=1)
        for_d_gen = np.concatenate([np.ones((batch_size,1)), np.zeros((batch_size,10))], axis=1)
        loss_d = discr.train_on_batch(np.concatenate([x_tru, x_gen], axis=0),
                                      np.concatenate([for_d_tru, for_d_gen], axis=0))
        if i % (print_every_nth_epoch*batch_size) == 0:
            print (i / batch_size, "discr", loss_d)
        pre_losses_d.append(loss_d)

loss, accuracy = discr.evaluate(x_test_dense,
                                np.concatenate([np.zeros((len(y_test_enc),1)), y_test_enc], axis=1), verbose=0
print("Loss={:.3f}\nAccuracy = {:.3f}".format(loss, accuracy))
```

Train the generator and discriminator together

```
losses_d = []
losses_g = []
for epoch in range(n_epochs):
    print ("Epoch", epoch)
    discr.save("discr-num-"+str(epoch))
    generate.save("generate-num-"+str(epoch))
    for i in range(0, len(x_train), batch_size):
        one_hot_gen = np.eye(10)[np.random.random_integers(0, 9, size=(batch_size,))]
        x_inp = np.concatenate([np.random.uniform(0, 1, (batch_size, nfeatures)), one_hot_gen], axis=1)
        x_gen = generate.predict(x_inp)
        x_tru = x_tru_all[i:i+batch_size]
        y_tru = y_train_enc[i:i+batch_size]
        discr.trainable = True
        for_d_tru = np.concatenate([np.zeros((batch_size,1)), y_tru], axis=1)
        for_d_gen = np.concatenate([np.ones((batch_size,1)), np.zeros((batch_size,10))], axis=1)
        loss_d = discr.train_on_batch(np.concatenate([x_tru, x_gen], axis=0),
                                      np.concatenate([for_d_tru, for_d_gen], axis=0))
        discr.trainable=False
        for_g = np.concatenate([np.zeros((batch_size,1)), one_hot_gen], axis=1)
        new_inp_g = np.concatenate([np.random.uniform(0, 1, (batch_size, nfeatures)), one_hot_gen], axis=1)
        loss_g = gen_discr.train_on_batch(new_inp_g, for_g)
        if i % (print_every_nth_epoch*batch_size) == 0:
            print (i / batch_size, "discr", loss_d, "--", "gen", loss_g[0], "( acc.", loss_g[1], ")")
        losses_g.append(loss_g)
        losses_d.append(loss_d)

print ("done")
```

Check the output of the labelled GAN

```
# generate = tf.keras.models.load_model('generate-num-41')

nim = 25
numb = 1
pred = generate.predict(np.concatenate([np.random.uniform(0, 1, (nim,nfeatures)), np.eye(10)[[numb,]*nim] ], a

plt.clf()
for i in range(nim):
    plt.subplot(np.sqrt(nim),np.sqrt(nim),i+1)
    plt.imshow(pred[i,:,:,0], cmap='gray')

pred[0].shape, np.average(pred[0])
F = plt.gcf(); F.set_size_inches((10,10)); plt.savefig("gen-num-img_after-%d.png" % numb); "gen-num-img_after-
```

Some examples from labelled GAN