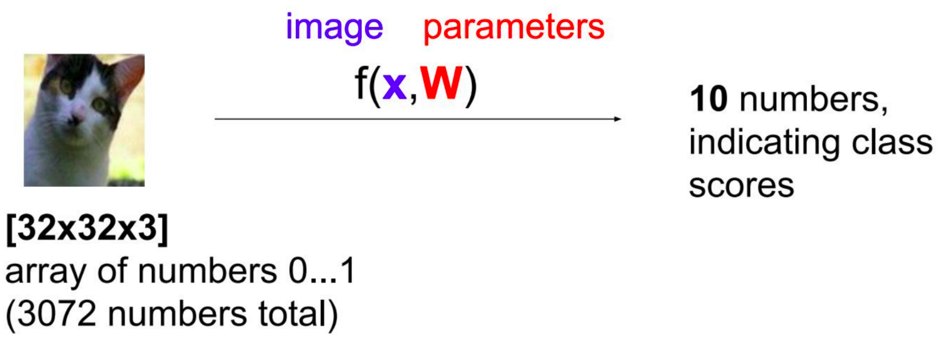
Deep Learning Seminar 1

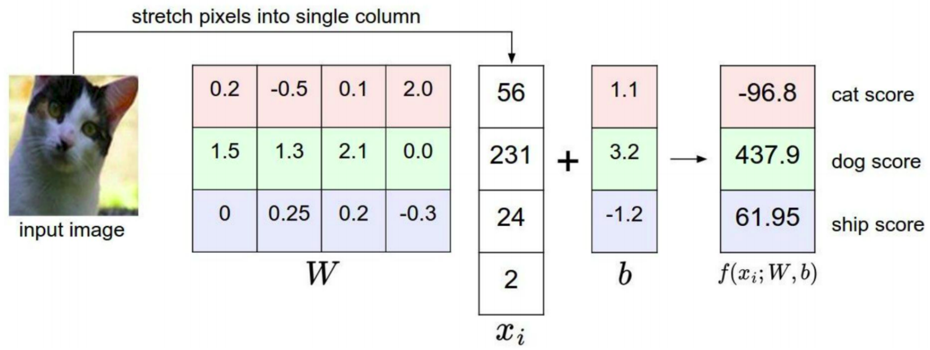
Credit cs231n.stanford.edu

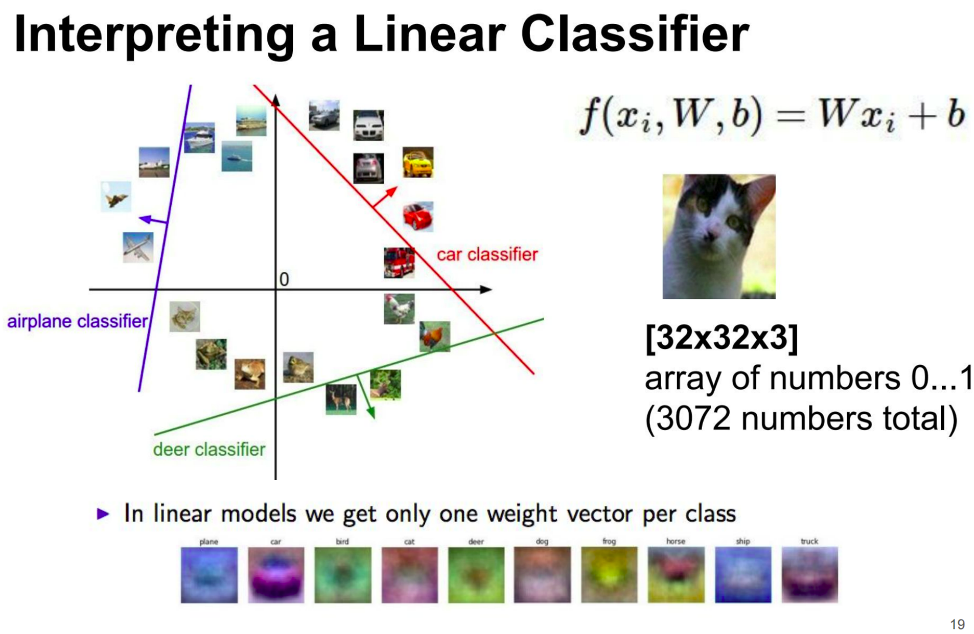
What was at Lecture?

- Image Classification

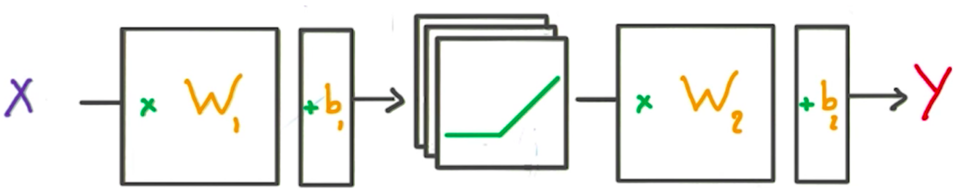


- Linear Models (Что делает линейная модель простым языком)





- Fully Connected Neural Nets



BackProp and Optimizers

In [3]:
```
import numpy as np
from scipy.optimize import check_grad
from gradient_check import eval_numerical_gradient_array

def rel_error(x, y):
        return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs
(y))))
```

Grad Check

Gradient Checks

In theory, performing a gradient check is as simple as comparing the analytic gradient to the numerical gradient. In practice, the process is much more involved and error prone. Here are some tips, tricks, and issues to watch out for:

Use the centered formula. The formula you may have seen for the finite difference approximation when evaluating the numerical gradient looks as follows:

$$\frac{df(x)}{dx} = \frac{f(x+h) - f(x)}{h} \quad \text{(bad, do not use)}$$

where h is a very small number, in practice approximately 1e-5 or so. In practice, it turns out that it is much better to use the *centered* difference formula of the form:

$$\frac{df(x)}{dx} = \frac{f(x+h) - f(x-h)}{2h} \quad \text{(use instead)}$$

This requires you to evaluate the loss function twice to check every single dimension of the gradient (so it is about 2 times as expensive), but the gradient approximation turns out to be much more precise. To see this, you can use Taylor expansion of $f(x+h)$ and $f(x-h)$ and verify that the first formula has an error on order of $O(h)$, while the second formula only has error terms on order of $O(h^2)$ (i.e. it is a second order approximation).

Softmax Loss Layer

$$L = \underbrace{\frac{1}{N}\sum_i L_i}_{\text{data loss}} + \underbrace{\lambda R(W)}_{\text{regularization loss}}$$

$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}}\right) \qquad \text{or equivalently} \qquad L_i = -f_{y_i} + \log\sum_j e^{f_j}$$

In [60]:
```
def softmax_loss(x, y):
    """
    Computes the loss and gradient for softmax classification.

    Inputs:
    - x: Input data, of shape (N, C) where x[i, j] is the score for the
jth class
    for the ith input.
    - y: Vector of labels, of shape (N,) where y[i] is the label for x[i
] and
    0 <= y[i] < C

    Returns a tuple of:
    - loss: Scalar giving the loss
    - dx: Gradient of the loss with respect to x
    """
    probs = np.exp(x - np.max(x, axis=1, keepdims=True))
    probs /= np.sum(probs, axis=1, keepdims=True)
    N = x.shape[0]
    eps = 1e-8
    loss = -np.sum(np.log(probs[np.arange(N), y] + eps)) / N

    dx = probs.copy()
    dx[np.arange(N), y] -= 1
    dx /= N
    return loss, dx
```

In [61]:
```
y = np.random.randint(0, 3, 10)
dx = lambda x: softmax_loss(x.reshape((10, 3)), y)[1].reshape(-1)
loss = lambda x: softmax_loss(x.reshape((10, 3)), y)[0]
```

In [51]:
```
print 'loss is a scalar\n', loss(np.random.random((10, 3)))
```

```
loss is a scalar
1.14194659231
```

In [52]:
```
print 'gradient is a matrix with shape 10x3\n', dx(np.random.random((10,
3)))
```

```
gradient is a matrix with shape 10x3
[ 0.03491482  0.0333956  -0.06831042  0.03047965  0.04580841 -0.07628807
  0.02213528 -0.07446436  0.05232907  0.03530645 -0.06458656  0.02928011
  0.04054461 -0.06266242  0.02211781  0.03118431 -0.0703896   0.03920529
  0.0302208  -0.07148604  0.04126525 -0.05965338  0.03647996  0.02317342
 -0.06878958  0.02024747  0.04854211  0.02234013  0.05394509 -0.07628522]
```

In [53]:
```
print 'difference should be ~10e-8', check_grad(loss, dx, np.random.rand
om((10, 3)).reshape(-1))
```

```
difference should be ~10e-8 3.62557041388e-08
```

Dense Layer

$$f(x_i, W, b) = Wx_i + b$$

In [15]:
```
def affine_forward(x, w, b):
    """
    Computes the forward pass for an affine (fully-connected) layer.

    The input x has shape (N, d_1, ..., d_k) and contains a minibatch of
N
    examples, where each example x[i] has shape (d_1, ..., d_k). We will
    reshape each input into a vector of dimension D = d_1 * ... * d_k, a
nd
    then transform it to an output vector of dimension M.

    Inputs:
    - x: A numpy array containing input data, of shape (N, d_1, ..., d_k
)
    - w: A numpy array of weights, of shape (D, M)
    - b: A numpy array of biases, of shape (M,)

    Returns a tuple of:
    - out: output, of shape (N, M)
    - cache: (x, w, b)
    """
    out = None

    ########################################################################
#########
    # TODO: Implement the affine forward pass. Store the result in out.
You     #
    # will need to reshape the input into rows.
#
    ########################################################################
#########
    N = x.shape[0]
    _x = x.reshape((N, -1)) # reshape the input into rows
    #print _x
    out = _x.dot(w) + b
    cache = (x, w, b)
    return out, cache
```

In [16]:
```
# Test the affine_forward function

num_inputs = 2
input_shape = (4, 5, 6)
output_dim = 3

input_size = num_inputs * np.prod(input_shape)
weight_size = output_dim * np.prod(input_shape)

x = np.linspace(-0.1, 0.5, num=input_size).reshape(num_inputs, *input_sh
ape)
w = np.linspace(-0.2, 0.3, num=weight_size).reshape(np.prod(input_shape)
, output_dim)
b = np.linspace(-0.3, 0.1, num=output_dim)

out, _ = affine_forward(x, w, b)
correct_out = np.array([[ 1.49834967,  1.70660132,  1.91485297],
                        [ 3.25553199,  3.5141327,   3.77273342]])

# Compare your output with ours. The error should be around 1e-9.
print 'Testing affine_forward function:'
print 'difference: ', rel_error(out, correct_out)
```

```
Testing affine_forward function:
difference:  9.76984946819e-10
```

In [21]:
```
def affine_backward(dout, cache):
    """
    Computes the backward pass for an affine layer.

    Inputs:
    - dout: Upstream derivative, of shape (N, M)
    - cache: Tuple of:
    - x: Input data, of shape (N, d_1, ... d_k)
    - w: Weights, of shape (D, M)

    Returns a tuple of:
    - dx: Gradient with respect to x, of shape (N, d1, ..., d_k)
    - dw: Gradient with respect to w, of shape (D, M)
    - db: Gradient with respect to b, of shape (M,)
    """
    x, w, b = cache
    dx, dw, db = None, None, None
    ################################################################
#########
    # TODO: Implement the affine backward pass.
#
    ################################################################
#########
    N = x.shape[0]
    D = np.prod(x.shape[1:]) # D = d_1 * ... * d_k
    x2 = x.reshape((N, D))

    dx2 = np.dot(dout, w.T)
    dw = np.dot(x2.T, dout)
    db = np.dot(dout.T, np.ones(N))

    dx = dx2.reshape(x.shape)
    return dx, dw, db
```

In [22]:
```
# Test the affine_backward function

x = np.random.randn(10, 2, 3)
w = np.random.randn(6, 5)
b = np.random.randn(5)
dout = np.random.randn(10, 5)

dx_num = eval_numerical_gradient_array(lambda x: affine_forward(x, w, b)
[0], x, dout)
dw_num = eval_numerical_gradient_array(lambda w: affine_forward(x, w, b)
[0], w, dout)
db_num = eval_numerical_gradient_array(lambda b: affine_forward(x, w, b)
[0], b, dout)

_, cache = affine_forward(x, w, b)
dx, dw, db = affine_backward(dout, cache)

# The error should be around 1e-10
print 'Testing affine_backward function:'
print 'dx error: ', rel_error(dx_num, dx)
print 'dw error: ', rel_error(dw_num, dw)
print 'db error: ', rel_error(db_num, db)
```

```
Testing affine_backward function:
dx error:  4.50319397853e-10
dw error:  6.65351379505e-11
db error:  1.31495834311e-11
```

ReLu Layer

$$ReLu(x) = max(0, x)$$

In [42]:
```
def relu_forward(x):
    """
    Computes the forward pass for a layer of rectified linear units (ReL
Us).

    Input:
    - x: Inputs, of any shape

    Returns a tuple of:
    - out: Output, of the same shape as x
    - cache: x
    """
    ########################################################################
#########
    # TODO: Implement the ReLU forward pass.
#
    ########################################################################
#########
    out = (x > 0) * x # if x_i < 0 then 0 else x_i
    #print out
    cache = x
    return out, cache
```

In [43]:
```
# Test the relu_forward function

x = np.linspace(-0.5, 0.5, num=12).reshape(3, 4)

out, _ = relu_forward(x)
correct_out = np.array([[ 0.,          0.,          0.,          0.,
],
                        [ 0.,          0.,          0.04545455,  0.13636
364,],
                        [ 0.22727273,  0.31818182,  0.40909091,  0.5,
]])

# Compare your output with ours. The error should be around 1e-8
print 'Testing relu_forward function:'
print 'difference: ', rel_error(out, correct_out)
```

```
Testing relu_forward function:
difference:  4.99999979802e-08
```

In [44]:
```
def relu_backward(dout, cache):
    """
    Computes the backward pass for a layer of rectified linear units (Re
LUs).

    Input:
    - dout: Upstream derivatives, of any shape
    - cache: Input x, of same shape as dout

    Returns:
    - dx: Gradient with respect to x
    """
    dx, x = None, cache
    ########################################################################
#########
    # TODO: Implement the ReLU backward pass.
#
    ########################################################################
#########
    dx = dout * (x >= 0)
    dx = dx.reshape(*x.shape)
    return dx
```

In [45]:
```
x = np.random.randn(10, 10)
dout = np.random.randn(*x.shape)

dx_num = eval_numerical_gradient_array(lambda x: relu_forward(x)[0], x,
dout)

_, cache = relu_forward(x)
dx = relu_backward(dout, cache)

# The error should be around 1e-12
print 'Testing relu_backward function:'
print 'dx error: ', rel_error(dx_num, dx)
```

```
Testing relu_backward function:
dx error:  3.27562862803e-12
```

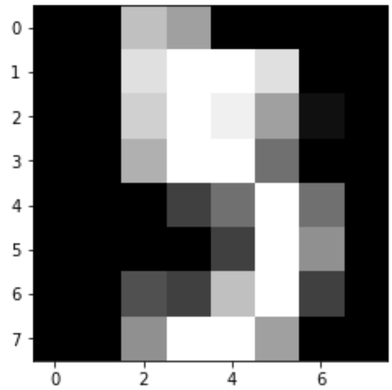
Two Layer Fully Connected Neural Net with SGD

In [58]:
```
from sklearn.datasets import load_digits
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split

%pylab inline

X, y = load_digits(return_X_y=True)
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7
)
```

```
Populating the interactive namespace from numpy and matplotlib
```

In [59]:
```
pylab.imshow(X[5].reshape((8, 8)), cmap='gray')
```

Out[59]:
```
<matplotlib.image.AxesImage at 0x7f6efe2c5c50>
```



In [56]:
```
W1, b1 = np.random.random((64, 100)), np.random.random(100)
W2, b2 = np.random.random((100, 10)), np.random.random(10)

lr = 1e-4

for i in range(50000):
    batch_index = np.random.randint(0, X_train.shape[0], 100)
    batch_X, batch_y = X_train[batch_index], y_train[batch_index]

    # ----------- Train ----------------
    # Forward Pass
    out1, cache1 = affine_forward(batch_X, W1, b1) # Dense Layer
    out2, cache2 = relu_forward(out1)              # ReLu Layer
    out3, cache3 = affine_forward(out2,    W2, b2) # Dense Layer
    tr_loss, dx = softmax_loss(out3, batch_y)      # Loss Layer

    # Backward Pass
    dx, dW2, db2 = affine_backward(dx, cache3)
    dx = relu_backward(dx, cache2)
    dx, dW1, db1 = affine_backward(dx, cache1)

    # Updates
    W2 -= lr * dW2
    b2 -= lr * db2
    W1 -= lr * dW1
    b1 -= lr * db1

    # ----------- Test ----------------
    # Forward Pass
    out1, cache1 = affine_forward(X_test, W1, b1) # Dense Layer
    out2, cache2 = relu_forward(out1)              # ReLu Layer
    out3, cache3 = affine_forward(out2,    W2, b2) # Dense Layer
    te_loss, dx = softmax_loss(out3, y_test)         # Loss Layer

    # Predict
    probs = np.exp(out3 - np.max(out3, axis=1, keepdims=True))
    probs /= np.sum(probs, axis=1, keepdims=True)
    y_pred = np.argmax(probs, axis=1)

    if i % 1000 == 0:
        print 'epoch %s:' % i,
        print '\t tr_loss %.2f' % tr_loss,
        print '\t te_loss %.2f' % te_loss,
        print '\t te_acc %s' % accuracy_score(y_pred, y_test)
```

```
epoch 0:        tr_loss 16.58   te_loss 16.65   te_acc 0.0944444444444
epoch 1000:     tr_loss 3.23    te_loss 3.49    te_acc 0.701851851852
epoch 2000:     tr_loss 1.80    te_loss 2.21    te_acc 0.803703703704
epoch 3000:     tr_loss 1.63    te_loss 1.26    te_acc 0.859259259259
epoch 4000:     tr_loss 1.10    te_loss 1.13    te_acc 0.875925925926
epoch 5000:     tr_loss 0.47    te_loss 0.94    te_acc 0.898148148148
epoch 6000:     tr_loss 0.77    te_loss 0.92    te_acc 0.901851851852
epoch 7000:     tr_loss 0.64    te_loss 0.97    te_acc 0.905555555556
epoch 8000:     tr_loss 0.48    te_loss 0.83    te_acc 0.905555555556
epoch 9000:     tr_loss 0.10    te_loss 0.98    te_acc 0.9
epoch 10000:    tr_loss 0.43    te_loss 0.96    te_acc 0.901851851852
epoch 11000:    tr_loss 0.77    te_loss 0.96    te_acc 0.914814814815
epoch 12000:    tr_loss 0.10    te_loss 0.68    te_acc 0.924074074074
epoch 13000:    tr_loss 0.87    te_loss 0.83    te_acc 0.909259259259
epoch 14000:    tr_loss 0.30    te_loss 0.68    te_acc 0.92037037037
epoch 15000:    tr_loss 0.14    te_loss 0.78    te_acc 0.911111111111
epoch 16000:    tr_loss 0.10    te_loss 0.67    te_acc 0.92037037037
epoch 17000:    tr_loss 0.24    te_loss 0.68    te_acc 0.92037037037
epoch 18000:    tr_loss 0.09    te_loss 0.67    te_acc 0.918518518519
epoch 19000:    tr_loss 0.20    te_loss 0.66    te_acc 0.927777777778
epoch 20000:    tr_loss 0.25    te_loss 0.75    te_acc 0.916666666667
epoch 21000:    tr_loss 0.11    te_loss 0.74    te_acc 0.918518518519
epoch 22000:    tr_loss 0.07    te_loss 0.72    te_acc 0.911111111111
epoch 23000:    tr_loss 0.09    te_loss 0.66    te_acc 0.922222222222
epoch 24000:    tr_loss 0.02    te_loss 0.65    te_acc 0.92037037037
epoch 25000:    tr_loss 0.06    te_loss 0.65    te_acc 0.925925925926
epoch 26000:    tr_loss 0.05    te_loss 0.65    te_acc 0.927777777778
epoch 27000:    tr_loss 0.05    te_loss 0.66    te_acc 0.92962962963
epoch 28000:    tr_loss 0.13    te_loss 0.65    te_acc 0.92037037037
epoch 29000:    tr_loss 0.33    te_loss 0.66    te_acc 0.925925925926
epoch 30000:    tr_loss 0.03    te_loss 0.62    te_acc 0.92962962963
epoch 31000:    tr_loss 0.11    te_loss 0.66    te_acc 0.924074074074
epoch 32000:    tr_loss 0.30    te_loss 1.00    te_acc 0.9
epoch 33000:    tr_loss 0.02    te_loss 0.62    te_acc 0.927777777778
epoch 34000:    tr_loss 0.04    te_loss 0.65    te_acc 0.92962962963
epoch 35000:    tr_loss 0.43    te_loss 0.90    te_acc 0.901851851852
epoch 36000:    tr_loss 0.19    te_loss 0.70    te_acc 0.922222222222
epoch 37000:    tr_loss 0.01    te_loss 0.65    te_acc 0.927777777778
epoch 38000:    tr_loss 0.01    te_loss 0.65    te_acc 0.92962962963
epoch 39000:    tr_loss 0.01    te_loss 0.65    te_acc 0.925925925926
epoch 40000:    tr_loss 0.03    te_loss 0.64    te_acc 0.925925925926
epoch 41000:    tr_loss 0.17    te_loss 0.78    te_acc 0.911111111111
epoch 42000:    tr_loss 0.00    te_loss 0.61    te_acc 0.931481481481
epoch 43000:    tr_loss 0.01    te_loss 0.63    te_acc 0.927777777778
epoch 44000:    tr_loss 0.07    te_loss 0.61    te_acc 0.931481481481
epoch 45000:    tr_loss 0.01    te_loss 0.66    te_acc 0.925925925926
epoch 46000:    tr_loss 0.02    te_loss 0.64    te_acc 0.933333333333
epoch 47000:    tr_loss 0.00    te_loss 0.64    te_acc 0.925925925926
epoch 48000:    tr_loss 0.00    te_loss 0.62    te_acc 0.931481481481
epoch 49000:    tr_loss 0.01    te_loss 0.62    te_acc 0.935185185185
```

What is the challenge?

You will see in Assignment 1:

- more layers and architectures (Dropout, Convolution, Pooling)
- optimization (Momentum, Adam)
- weight initialization
- data augmentation
- ...

!!! Отзывы о лекции goo.gl/gMeYNL о семинаре goo.gl/5hlPD0 !!!

In [ ]:

```

```