MNIST from scratch

This notebook walks through an example of training a TensorFlow model to do digit classification using the MNIST data set. MNIST is a labeled set of images of handwritten digits.

An example follows.

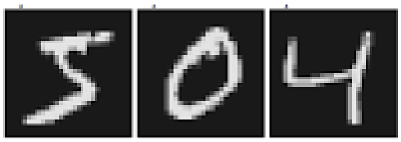
```
from __future__ import print_function

from IPython.display import Image
import base64
Image(data=base64.decodestring("iVBORw0KGgoAAAANSUhEUgAAAMYAAABFCAYAAAARv5krAAA
Yl0lEQVR4Ae3dV4wc1bYG4D3YYJucc8455yCSSIYrBAi4EjriAZHECyAk3rAID1gCIXGRgIvASIQr8U
TmgDA5imByPpicTcYGY+yrbx+tOUWpu2e6u7qnZ7qXVFPVbv2Xutfce+q7hlasmTJktSAXrnn8vR/3
/xXmnnadg1aTfxL3/7rwfSPmT+kf/7vf098YRtK+FnaZaf/SS++OjNNathufF9caiT2v/xxqbTGki/S
XyM1nODXv/r8+7Tb+r+lnxZNcEFHEG/e3LnpoINXSh/PWzxCy/F9eWjOnDlLrr/++jR16tQakgylqdO
WTZOGFqX5C/5IjXNLjdt7/NTvv/+eTjnllLT//vunr776Kl100UVpueWWq8n0lOmpSmTU5o/f0Fa3D
DH1ry9p0/++eefaZ999slYYPS0005LK664Yk2eJ02ekqZNnZx+XzA/LfprYgGxePHitOqqq6YZM2aky
fPmzUvXXXddHceoic2EOckxDj300CzPggUL0g033NC3OKy00krDer3pppv6FgcBIjvGUkv9u5paZZVV
hoHpl4Mvv/wyhfxDQ0NZ7H7EQbacPHny39Tejzj88ccfacqURKRmHEecYf0Nr8GGAQJ8gMHCMPlH0QMz
mEBg4RnN4DVr3CQIDx+gTRQ/EbA6BgWM0h9egdZ8g8PeliD4RutfF/Ouvfz9OtZy8aNGiNH/+/GGWl1
122XzseYuVNKtqsaI23Ghw0DYCA8doG8JqO+AUG2+8cVq4cGHaY4890vLLL5/WXXfdfI6jvPDCC3lJ8
amnnkoezP3000/pl19+GThHtWpIPekYomTxFS7HnkqKjMsss0yGgFE4r62tSBFVJ02aNPyconi9V4/J
wzHwT9ZNNtkkeZ6w5ZZbph133DH99ttv6ccff8zXX3nllbRcRnHNv2cNGMQWGRaOrWbUrjsGBRLAA6U
4Lhoqw9h2223ztRBq6aWXzsbgvueffz4Lu9NOO2UnYTgrr7xy7y7t09nOH111/Pbb744ov0ww8/jAvngA
dFMvQDDjggG/0GG2yQZXm1GZNm1aziCCwzrrrJPl3muvvXKwePnll9M333333wzHDCKWPbLMbuAkfISjnvvv
XcW/emnn85lqCBqa4a65hiYR/Gk2RNGRlwm3n8+qCBqd8+umn6eeff84Bspmswuu3NnvJfffXmDtT7GeXmPYeuut
c0SVNQjvnmuvvTa3efefzx77DBvvqq233qviNN1PuIdJ4GErVx44YUZOwm0/uR+6vmqviNN1PuIdJ4GErVx44YUZOwsuuCB9+umn6eeff84BspmsWqljhPFDxjGGYx/lDk
N33udajCoVlAjRzl4U8LjefRwnPjsXG8OJqKBd8NB1LTU5IHyCd7LJGOYXNoGjFqaGIKtrERDIDKtuk
fGMH/zRZa1A101+YBF44KfMYzO8VOYYjDWiukiGqc022yyXOUqdzTffPJPJPJ/z1ialeqNVxA9gi0wzlOJ5
juJlR8JeddVV+ZrIKTq4ZvJp/8EHH+SU+txz+W2SqmxVFZRplrH5DTRXmGFFdKuu+6azjjjjjjOzosl5
g6D54CQCI4mGjhNQO5occckh2LvLTA6fqJOEnyhU6kNlkZmUuvrtNcFx77bUzhsSZWXgoSsm6t4Dsa/t
p2DErCmA04HAI4FLjaaqtlBhmnSKiNY4rDtHZFB6jFMMH0RVDH+nCPYxtDCFJnKkniRbDitWjTK3syk
QUuMLPn3DZGX8SFnCG/fVyz5zCCBtIHTLshdzif8fERn8cKXxjCNOwCTu3Qf6yqhV4AQokiP489//zz
M0DxnQYKwqAtIkko1kQzFFxvaNcJ6u3Pe+65J/cRRvff+2BdsJxGL2xbhgtIi2ZLrd6sjm8/yNBXo0
WynmyiPJ43WKLLbIijz/++lTddtvlTCdzwIWSg9yjxBJ0GN/DDz+c7zv77PhAy1PpVb4Qe5H1iS+cmLDLW//bLczBdceW+SekwVGgsOsWb
```

```
NyNo0+qt7DfPvtt8/dmtvIGnPnzk3PPPPMsJ6rHrNef/BBeJA90RprrJEDcNhctMkXR/mnbccwuCjNG
TbaaKMc8TBZprITxOdgOvbuKxqGz6LSJ598kseJ9Gi1CYmSv/76a3YyJZWMZJ6Ceskp8EMusihFEAyU
mVaa8G2rxTNHIrd733///eH7YeaLNe5xrEzlWNF/HqQDf0Tm+GIbvYdD43MsKAIo/JDgE0G5aFfN8Na
WYxiUshikqGYTTUSt0TCkjXsYNqJQQso+rgGa0vX58ccf56hQTtk+48F92rmvlnE1A0on2uKP0Yrw+N
xzzz0zn+ZhjKwRXq6vueaa2TmUiRQfS7SyNeMks9IV9vrvJOl/q622yo4Mfw5Pvm6TMclLdit6shh+Y
AMnq1E29tEsteUYBgMSgxa5MOAzJZcVXQs4bUR8XxhCHIwzMALCBuCcx5q0tF3u133l8XrRMchFiRYN
yMxBKM/5IjZlWVzjULKwACISytIWFsi56aab5mvOKyEikmdAO/iHY+BDCRUZuoPD1e1akECyLseA7d1
3352DhdKak8Cmlt3U7TSl9p58FwejYK8ncAwKpDTnGDcARbWiAUjHiNEHsITSPlagpEZChcfrZzwSOf
BOiQwXLuR3PjAhtwAD08iAMCO/a+5xPTIm3ALjwERf0V+c69QeT7ZujVdLDhgKBrANXAMreMESRkU7r
dVPrXNtZ4xIpSLH1VdfnR3j4IMPzkbw2Wefpa+//jovo5188slZsZjArAcvFP3YY4+lSy+9NEdTdTTy
0I5xHHfccfm1CH2LtuORKEqmkwVlVU+sBY+IdJRmE0zeeOONnEXuu+++7AhnnnlmWn/99XMJ5brtzTf
fzHMJx/o555xzkgdb0U8rRtAKrnTYqtG1Ml6teyxInHDCCdlGYByBmG2Z97ChVvFo2zEwbHCRTbqP7E
DxPjN2pUBEe86AXAcsg+f10TYMSTvnRM1ulQe1wG/nHEXZZEJZUIYQ5cgWMsEgMgqclFdkdh+MbFFyu
ddnWMLNfTYkcuuXHlBkpFYNI3dS+mMMfCHHsZWadfUjmQVn8iLywscG21apMscQwR555JEM3KuvvpoZ
5LHOmzgjAvBwzFt2/Oijj3Lm4Ayin/MU/eGHH+b2N998c/5MGSaZ44nw7OEd5Rx77LE5+1EehYXxkpe
s5li2K6+8Mhv8Lrvsko381ltvzcEBfvHQKh5auk9GPvHEE3NJAx+/eKL/HXbYIQcbK3nwN067xAk4s5
VHdbvsx0nxrYQeKxJMZAfBA7GlRx99NC9EtCN7JY4RoPBeAHIAyrB3jpHYwqu1d02d7HpZcfqINo5dL
7eJMXtxTzk2sgWFM/gcsnCakI2cFOk+5230+Qw7WaeYHYpYRp9xn4BkbPdWSfgJXYYM+ne+2xRj2sdx
8EDu8rm4Ntp9pY4RSmb0CIPOAVNGoLA47yU4S2xen37ppZdy9CkLE/3lm8bJHzJbbiavt2Q9p7AkK7o
yXAZOLk7gs9c4PJC0AOE8DDyrgJkaWgYQkSPYuAdpWySfteU8HhqKouYq+io6ZfGeZo7xpbT1+jt+jG
ULfprpq922ePHMBibwjWVq523KVrzBsIzTaMeu1DFi0HI0YyyYtAekY5MltbRyihFJiROBKIYTwMCTW
JNubwdQFCXFapK9z96mtbjgs3thFKWnUgjBzNZIya5FOyUcPG36q4LwRgZ6Ix8HtBk3tirGGU0feAks
lHfk5PzBh2cXSkvtWqWOOEaRGcoSHdXDMoYn1tK8yaON0ahbCWgFS/vxSnjn5F4ItLeiFAGAzCKc7MD
A1OlIjc4pLFKE7FEyxb5ZPNTbtuiv2fvrtddfOFsYXcwj8d8qv/XGq3femLvvvnvOvrIYPPEjG+PDse
DbDnXcMXiyiGiyyACOPvrovN95552zV3/++ef5zVveznlEo6CICvG5l/d4JSvHP+qoo7JjKDs4sGeslGW
Pm9HSz9W5rlPEoCQYHjVFXyRGnBOcKA28VOP/qTBWX6YnS2IKB8qYL/enyGHPbKziOOOCLj6sGeslGW
8L6Y4ANr2MY99fpsdL7jjmFwkSTSr6gDVCk+tmDQedcJ5LgdwaLPbu7xjJRRNlErSsiQhVHJlOEQoh1
82o1wRTnharwYs3itnWP9Rd/RD5mLW5yveh/YRhYMjItyBh/wjPat8tEVx6B00RKo5513XpIl7rzzzu
wEourMmTOz95uIcyBfTSXYiy++mCOrSFS1klsFrNZ9eGPoJtmeyRx00EE5cpGbIi21XnbZZbkMee211
7KMHIKMIVcotVb/vXoOz6I0+URoMlVFcBFE7L1+IjNYIo6v/fo+D3tC+FCR+FHuwNUCgfOtUlccI5hn
JMoIBhN1sBICqMoNNaLP3pkiFGciIIBC4HaEbRWk0dyHb3Mp/EY0I6+NsytvyKxsKhpQr8ozGpm1IZ8
IbV+PyllGuyh1YBXXOQEcy6R8M5eAHzuxxX3GRvbaCKJ4aRfXrjkG5jEbk00Prxi8SZTJKmc5/PDDc5
v99tsvC+hBjWtqStmD0F4Ma1foMvDtfqZMUc3/lYjMSFFW3NS7JtyyoKzSiTocHoFJHMc+MlK7Mta7n
9NbATJerbEYvQWIWCVitIyaXrV3nsG7H2Y2GVcbxyj6NX+waKEPmOvbfShwtjhQDDz5Ygt/uuoY+OPt
nICDEMBTWsAQUu0NBBsDEgFEWOADAiDaVRERWsCq5i34IRN+TbTJgn8KwzOFuR4KDUXW7Kyik53Ep8w
/+RkxWeO5S1EM5wVABguXMGp69dk1x87D0ObdL32GHI5tsDQGHtwbm/Hw4TpnKvNY5Ge0x113DEwT3t
IsIdSnDIfxcxJAevCHfE9cXcmotHXfAw88kIFUdgFjLMn4HuZRuh9FExmjRCCnZxRqcPxz8ioUVk9eR
hJkPAYHV8ZVFRkjjFSfAtw222yTy2OZ0iv15fHcQ4dKaMcwsBdEEL26RzaIh5+yK7LSBGPno8yOZX+v
zRhfXzZ8cRrtyzzkzpr803XHwB8wTJYIRol+VY8zqMMBbP0f+cExE1qTdbU7x3jwwQdzVBYdesExKNi
EWx2MfwoOAyCbJ9uRHZvUTcPmsENhGNE4HBKOHKNqZzQu3KNfX9H1nRABQZlbNkpt4SNo4DWIIesDj9
```

```
qYnwki2giWqol3330348kZLPm7xvi1Pffcc7MzhA3gy/0oeIuxWtmPiWNgNCIFYwcCAa2FA1ikJZz1a
eUVsBmge9TyoqGoIqKUFdEKCFXcU0/pHJizVMUnXBiBh6IicdTTzsEOnuZkDE/2rcJI4KMf/TF+0Tuc
wDhkZ+DGL4/nGkPGV/AIC+2RvfP6ZPTI4gu5XNM/Um7RPzuIFyn1zW7wpQ9UHj+fbOHPmDlGCOGBGIe
QQfwuq0jnISBQfOHft7JEHN94Q5xF6XLFFVfkyKIEGyuiGAo3r6BIx0imcM6k+6GHHspOEQbcDq+UTl
4BwRu7PstUiPEJFsa9/PLL83nXg6d2xnUvoxS5L7744uGyh/wyRpRF9YwSHsHjE088kWWADQeRFThZk
TgBstensZG5h4m56oEdcAp9CwTOVUlj6hgECcGBpA6XDazeiLKhVABQAhKB3cNxbEAL4KoEppm+gjf3
OMafDf+UW7zeTL/ltqIiAxBMOIIxnLOHgbFsMGQ4InhE0nJfrXw2hnIRD3SFBKmYWDfqE49woFvOzZn
o3NxM0HDciMjBDsjEBgLTsJHYN+qjmWtj7hjBLKFFQgL7qRz14jHHHJPBcC2M3wRPVDT5ohzZRv0Z16
O/sdozAKmdopUH5kftTrzJpl+lk29CcgpLw3BgpMbwwqF/S80pGJ6xO0WM+8Ybbxw2TuOEoTYakwyov
B/JKdzDMVQOHvCRzXju890fL11aGhcMqqIxdwwCRkYQDZAaE7lWBhyosQEmQM439MgffDHm0Si8EcuB
C0ezcQSZVKYktzFEW+3sfQ4natRvu9eMTS9F7IvHo+m/2fb6LNuCc0WsW+mzHq9j6hgE9YCHp5tkez2
EAVjlMOmyUlU2Lis8ygVR0rykyoltPZCaOY9fr32Qp50X6xi7pWCGbsHBvwLgGIcddljGxvcsjOU1Gs
eyiKjJQWydpiqNsBlei85BfhNxeJunVCl31x0jBOMAjJ9jRC3OEERDS7QMI0qQohIYgLSq7FJuMZbi9
WZA7kRbvFAWx5Dyy449mjEDG/dyDPW4VSiy2iNvBcCSUdxyyy35OYHrqJUx843j8I/qQpA074BVVdR1
x+AIHCIiIGewsqIuds41tSSlOxeOFHuOQ/E+2zPEuFYVKM32U3RMvGy44YbZMTg2B2+GOIXXJcjpR9l
kUy/QyZ7GUU8zAD9RCiuR0oQYVv1IMAk7qFL+rjkGg7GZQPLufffdN69QKJtkCAKKjNGu1p7gMgWDYE
DRpkpAmu0rnMLehie/RavcI49Sr1ZW0w6V91ac/IsxmdHPB0U5pQ+4+TExDudNUhPufnaKIn7N6m2k9
h11jKLRqP+UQJb2eHh4uYjK0LW1D0MpCq0NR4g24RTR/0hCdvM6/m14FtljeTL4D/liedFeO7LYcyh7
eMGDY8X16IM8Vp9kWjj2GwWG5IZb2FKVOHTMMTCvDKBgD2Z22223bNynnnpqVrZXBFxjQDZUFJiwIqK
HN8qHO+64IxvN/fffn9vG/VWC0UpfeC5uZMEbg/ctM/8SzYOxZ599Nhs4ebSx0ECpcDFvMCdRggkeso
Q+zaHU0N4EgAEnue2227JTON+LgaEVDFu5h+w2Wdl33GFkEUIQqYIqdYwwbJGO8q2xOydqUiTFWpJVP
zsuUwhlzzFETxlGdFSCqaMB4XwvUzgKWU3AyW4uwFns4QMbilUyxbq8p/4cw3UEB8FDGQUDx/acqB8z
RS2dw5qthe3VatPKucocg6JiYu3lP2nfawvekKVITzgJQLH24QTBtPZeE2D89957b27jwZ1IwIm8R2O
MWHmJ+3pxTzaK8l+HyMrgTzrppMxqOIEsGoZvz0nsyWiliRMUl2G9aOk6POyLZVUvYtBpniL4wA1m9l
VSW46BOQqKpTLK9FnUsxftvW4swssa4dkhCGFCMNfcp08lhM9KKc4h0obgsa8ShHb6Cv5DJnu8IwHB9
TB852DkOlzIRV6kXbSVMfQj48BWdhE0TLr1Fe3zQR/+gRMK5yjuq4KjZccQ2SlYjexHmCnSkiLjtses
mlnpQ5naFo1A5GMAHoJxBI709ttv54ygntZWmWEcQMS9VQleRT9kNmfAG0P3HRPGbHnVudg4gEyJOAY
iE0wikHAAcxHyxndO4KI/WHEK/Qzo7wjAXfaFNdurikaNtIERRTqmYIYdE2tGEs8hfJ8iFB/3xV67MC
jG8NZbb6Unn3wyC+XfDxfnDxFp496qhK6qn5CDA5twK/fIRH5Gb0MMOhxCFgkKjOBoHqKEkmWvueaan
G04iTHcP3CKQO0/e3ZhgceP2smqcKyKRuUYlEKhPDL+d5z1c4qVFTDnmBIZMwZ9DiKAzTmvCetPNFR7
W7fXXt/KLddqTcyjr17bRybkEF5XiQhPHnMuDlF07MCB3I49l4EDxTrnfsFBJBxQbQSKeGoROqjdurW
zIzoGJqRxS2KUf/rpp2flcRDRjRKVCdpFhCwz7rOVKE5z++235/7uuuuuXDq5P5yKEY0np8B3TKb9K1
/vLTF0/7MiJtyRPYrq4fx+7R2e7vFDDzDyfx1goPwcUGMEYG/rFI3oGAYW0UUyimQIcRwGzbgpVsZAU
TYE065xCtc5GUeSHTyg4kzKs/FKoSBljyhvTz6y2gseZAwlwgI+cNBGtpV9ZRj4BobjFY9O8g0bQcXW
aRpxBE5hHuFnJ0XB6dOn56ge2QGDlK2dFSSG4b8kxVzEdSWGVxgYQLzrxJkIGgbTaUE73b9MZ/KNfIM
OJpdcckndYZWmFAwv+wgydW/o8wsCK3xnz56dFzx8oxPGtk7QiI5h0FBaeGzRKYIpjDN2ig6lB9Oipr
mI60qNieIMIXvsQy7yotjH9eI+2hbPDY4bI8D+2JdnWTYY+iwDs78qaUTHEM0sI1pClAVMnqX9ImGQs
zB6DHoNOLzZNZlGRlEq9JNB9JOsRXvoxDGnsDTudwFUHTNmzMjDqEaU9xYvGgWiZnka0TEo16CeNyCM
1SLtwmt5cNEoCOUa5xjQAIFWEGBP5rbKdTRr1qwcfGUMthXVTCt917pnRMdwE6ZiQm0JckADBMYCgWL
wtXjTSeq/d5Y7ieag7wmDwMAxJowqB4JUicDAMapEc9DXhEFgcjxcM7vvR4on7bHS1q84WNkpUr/iEL
```

```
+aOLRw4cIlQCmuIhUBmsjHlpQ9c7EmzjEsN1vd6DeCg8UVT+qRd7b6EQey8wMT+6El8RSu36xhIO8Ag
QYI9F94bADG4NIAgUDg/wHX+3lgThDIegAAAABJRU5ErkJggg==".encode('utf-8')),
embed=True)
```

```
/opt/anaconda3/lib/python3.5/site-packages/ipykernel/__main__.py:5:
DeprecationWarning: decodestring() is a deprecated alias, use decodebytes()
```



We're going to be building a model that recognizes these digits as 5, 0, and 4.

Imports and input data

We'll proceed in steps, beginning with importing and inspecting the MNIST data. This doesn't have anything to do with TensorFlow in particular -- we're just downloading the data archive.

```
import os
from six.moves.urllib.request import urlretrieve

SOURCE_URL = 'https://storage.googleapis.com/cvdf-datasets/mnist/'
WORK_DIRECTORY = "/tmp/mnist-data"

def maybe_download(filename):
    """A helper to download the data files if not present."""
    if not os.path.exists(WORK_DIRECTORY):
        os.mkdir(WORK_DIRECTORY)
    filepath = os.path.join(WORK_DIRECTORY, filename)
    if not os.path.exists(filepath):
        filepath, _ = urlretrieve(SOURCE_URL + filename, filepath)
        statinfo = os.stat(filepath)
        print('Successfully downloaded', filename, statinfo.st_size, 'bytes.')
    else:
        print('Already downloaded', filename)
    return filepath


train_data_filename = maybe_download('train-images-idx3-ubyte.gz')
train_labels_filename = maybe_download('train-labels-idx1-ubyte.gz')
test_data_filename = maybe_download('t10k-images-idx3-ubyte.gz')
test_labels_filename = maybe_download('t10k-labels-idx1-ubyte.gz')
```

```
Already downloaded train-images-idx3-ubyte.gz
Already downloaded train-labels-idx1-ubyte.gz
Already downloaded t10k-images-idx3-ubyte.gz
Already downloaded t10k-labels-idx1-ubyte.gz
```

Working with the images

Now we have the files, but the format requires a bit of pre-processing before we can work with it. The data is gzipped, requiring us to decompress it. And, each of the images are grayscale-encoded with values from [0, 255]; we'll normalize these to [-0.5, 0.5].

Let's try to unpack the data using the documented format:

```
[offset] [type]          [value]          [description]
0000     32 bit integer  0x00000803(2051) magic number
0004     32 bit integer  60000            number of images
0008     32 bit integer  28               number of rows
0012     32 bit integer  28               number of columns
0016     unsigned byte   ??               pixel
0017     unsigned byte   ??               pixel
........
xxxx     unsigned byte   ??               pixel
```

Pixels are organized row-wise. Pixel values are 0 to 255. 0 means background (white), 255 means foreground (black).

We'll start by reading the first image from the test data as a sanity check.

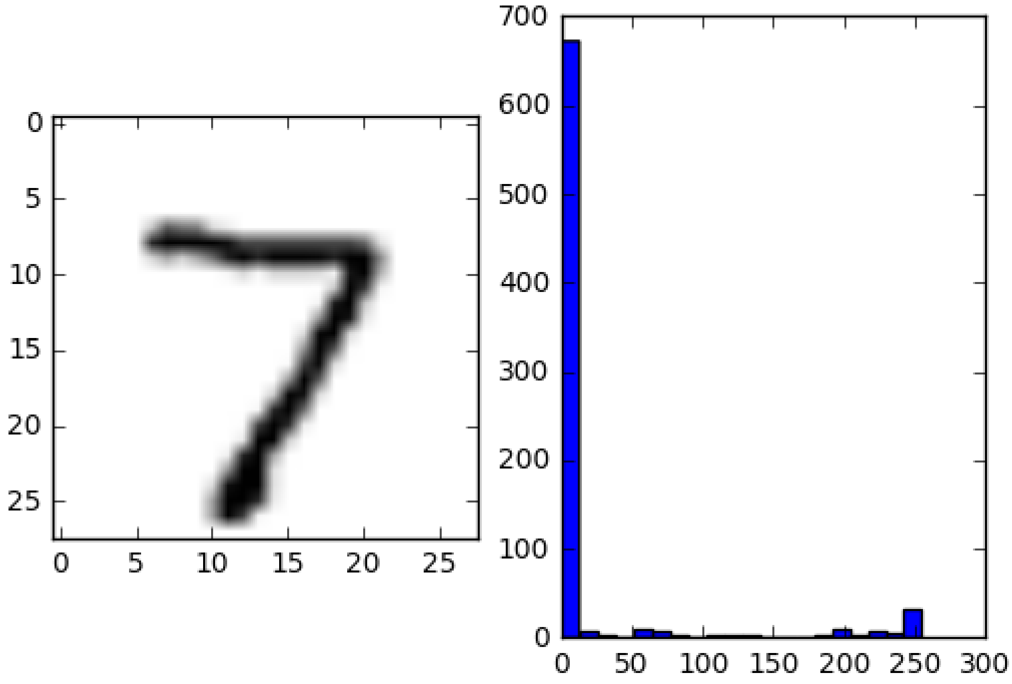
```
import gzip, binascii, struct, numpy
import matplotlib.pyplot as plt

with gzip.open(test_data_filename) as f:
    # Print the header fields.
    for field in ['magic number', 'image count', 'rows', 'columns']:
        # struct.unpack reads the binary data provided by f.read.
        # The format string '>i' decodes a big-endian integer, which
        # is the encoding of the data.
        print(field, struct.unpack('>i', f.read(4))[0])

    # Read the first 28x28 set of pixel values.
    # Each pixel is one byte, [0, 255], a uint8.
    buf = f.read(28 * 28)
    image = numpy.frombuffer(buf, dtype=numpy.uint8)

    # Print the first few values of image.
    print('First 10 pixels:', image[:10])
```

```
magic number 2051
image count 10000
rows 28



columns 28
First 10 pixels: [0 0 0 0 0 0 0 0 0 0]
```

The first 10 pixels are all 0 values. Not very interesting, but also unsurprising. We'd expect most of the pixel values to be the background color, 0.

We could print all 28 * 28 values, but what we really need to do to make sure we're reading our data properly is look at an image.

```
%matplotlib inline

# We'll show the image and its pixel value histogram side-by-side.
_, (ax1, ax2) = plt.subplots(1, 2)

# To interpret the values as a 28x28 image, we need to reshape
# the numpy array, which is one dimensional.
ax1.imshow(image.reshape(28, 28), cmap=plt.cm.Greys);

ax2.hist(image, bins=20, range=[0,255]);
```



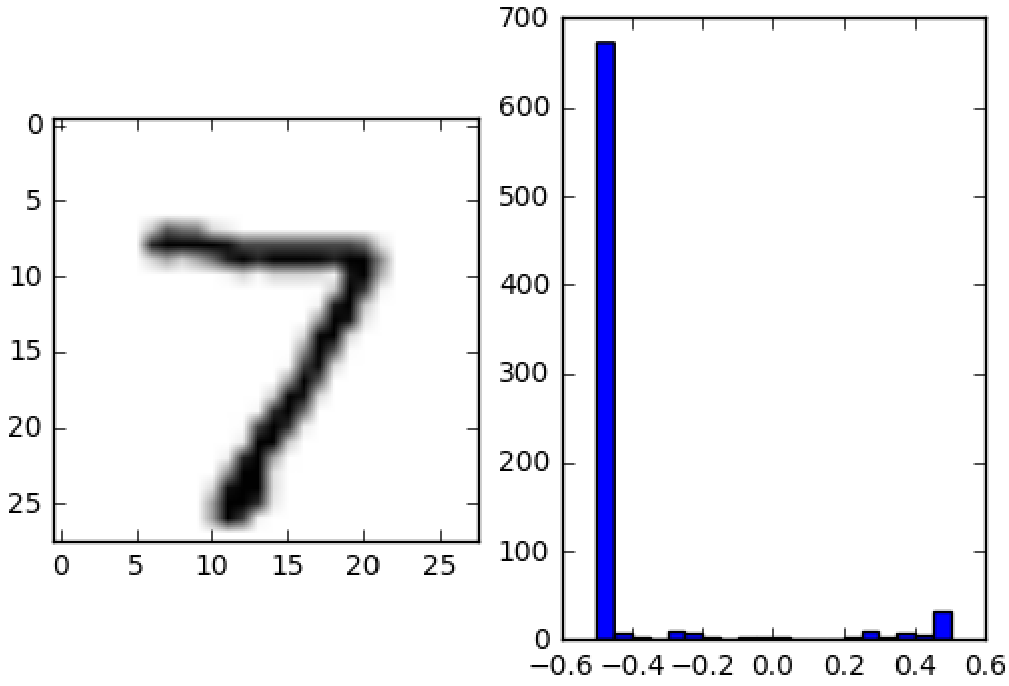
The large number of 0 values correspond to the background of the image, another large mass of value 255 is black, and a mix of grayscale transition values in between.

Both the image and histogram look sensible. But, it's good practice when training image models to normalize values to be centered around 0.

We'll do that next. The normalization code is fairly short, and it may be tempting to assume we haven't made mistakes, but we'll double-check by looking at the rendered input and histogram again. Malformed inputs are a surprisingly common source of errors when developing new models.

```
# Let's convert the uint8 image to 32 bit floats and rescale
# the values to be centered around 0, between [-0.5, 0.5].
#
# We again plot the image and histogram to check that we
# haven't mangled the data.
scaled = image.astype(numpy.float32)
scaled = (scaled - (255 / 2.0)) / 255
_, (ax1, ax2) = plt.subplots(1, 2)
ax1.imshow(scaled.reshape(28, 28), cmap=plt.cm.Greys);
```

```
ax1.imshow(scaled.reshape(28, 28), cmap=plt.cm.Greys);
ax2.hist(scaled, bins=20, range=[-0.5, 0.5]);
```



Great -- we've retained the correct image data while properly rescaling to the range [-0.5, 0.5].

Reading the labels

Let's next unpack the test label data. The format here is similar: a magic number followed by a count followed by the labels as `uint8` values. In more detail:

```
[offset] [type]          [value]          [description]
0000     32 bit integer  0x00000801(2049) magic number (MSB first)
0004     32 bit integer  10000            number of items
0008     unsigned byte   ??               label
0009     unsigned byte   ??               label
........
xxxx     unsigned byte   ??               label
```

As with the image data, let's read the first test set value to sanity check our input path. We'll expect a 7.

```
with gzip.open(test_labels_filename) as f:
    # Print the header fields.
    for field in ['magic number', 'label count']:
        print(field, struct.unpack('>i', f.read(4))[0])

    print('First label:', struct.unpack('B', f.read(1))[0])
```

```
magic number 2049
label count 10000
First label: 7
```

Indeed, the first label of the test set is 7.

Forming the training, testing, and validation data sets

Now that we understand how to read a single element, we can read a much larger set that we'll use for training, testing, and validation.

Image data

The code below is a generalization of our prototyping above that reads the entire test and training data set.

```
IMAGE_SIZE = 28
PIXEL_DEPTH = 255

def extract_data(filename, num_images):
    """Extract the images into a 4D tensor [image index, y, x, channels].

    For MNIST data, the number of channels is always 1.

    Values are rescaled from [0, 255] down to [-0.5, 0.5].
    """
    print('Extracting', filename)
    with gzip.open(filename) as bytestream:
        # Skip the magic number and dimensions; we know these values.
        bytestream.read(16)

        buf = bytestream.read(IMAGE_SIZE * IMAGE_SIZE * num_images)
        data = numpy.frombuffer(buf, dtype=numpy.uint8).astype(numpy.float32)
        data = (data - (PIXEL_DEPTH / 2.0)) / PIXEL_DEPTH
        data = data.reshape(num_images, IMAGE_SIZE, IMAGE_SIZE, 1)
        return data

train_data = extract_data(train_data_filename, 60000)
test_data = extract_data(test_data_filename, 10000)
```

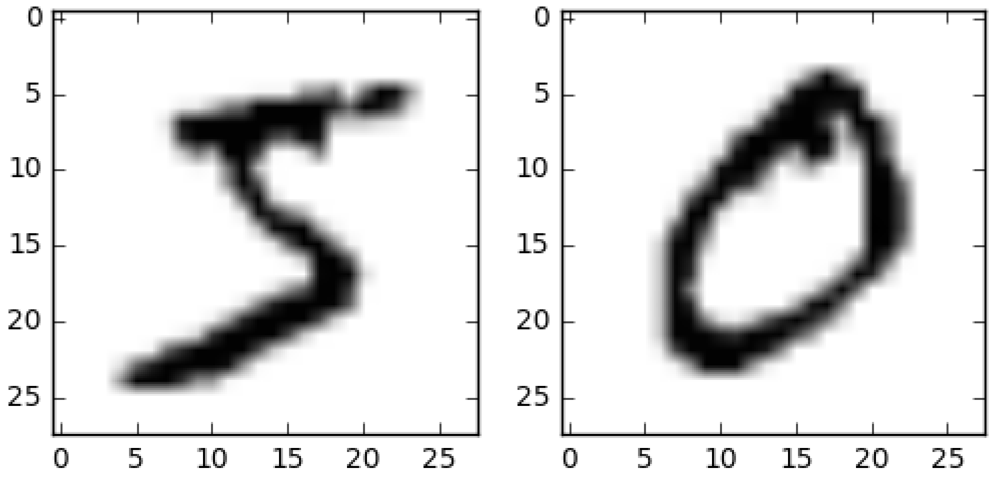
```
Extracting /tmp/mnist-data/train-images-idx3-ubyte.gz
Extracting /tmp/mnist-data/t10k-images-idx3-ubyte.gz
```

A crucial difference here is how we `reshape` the array of pixel values. Instead of one image that's 28x28, we now have a set of 60,000 images, each one being 28x28. We also include a number of channels, which for grayscale images as we have here is 1.

Let's make sure we've got the reshaping parameters right by inspecting the dimensions and the first two images. (Again, mangled input is a very common source of errors.)

```
print('Training data shape', train_data.shape)
_, (ax1, ax2) = plt.subplots(1, 2)
ax1.imshow(train_data[0].reshape(28, 28), cmap=plt.cm.Greys);
ax2.imshow(train_data[1].reshape(28, 28), cmap=plt.cm.Greys);
```

```
Training data shape (60000, 28, 28, 1)
```



Looks good. Now we know how to index our full set of training and test images.

Label data

Let's move on to loading the full set of labels. As is typical in classification problems, we'll convert our input labels into a 1-hot encoding over a length 10 vector corresponding to 10 digits. The vector [0, 1, 0, 0, 0, 0, 0, 0, 0, 0], for example, would correspond to the digit 1.

```
NUM_LABELS = 10


def extract_labels(filename, num_images):
    """Extract the labels into a 1-hot matrix [image index, label index]."""
    print('Extracting', filename)
    with gzip.open(filename) as bytestream:
        # Skip the magic number and count; we know these values.
        bytestream.read(8)
        buf = bytestream.read(1 * num_images)
        labels = numpy.frombuffer(buf, dtype=numpy.uint8)
    # Convert to dense 1-hot representation.
    return (numpy.arange(NUM_LABELS) == labels[:, None]).astype(numpy.float32)

train_labels = extract_labels(train_labels_filename, 60000)
test_labels = extract_labels(test_labels_filename, 10000)
```

```
Extracting /tmp/mnist-data/train-labels-idx1-ubyte.gz
Extracting /tmp/mnist-data/t10k-labels-idx1-ubyte.gz
```

As with our image data, we'll double-check that our 1-hot encoding of the first few values matches our expectations.

```
print('Training labels shape', train_labels.shape)
print('First label vector', train_labels[0])
print('Second label vector', train_labels[1])
```

```
Training labels shape (60000, 10)
First label vector [ 0.  0.  0.  0.  0.  1.  0.  0.  0.  0.]
Second label vector [ 1.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
```

The 1-hot encoding looks reasonable.

Segmenting data into training, test, and validation

The final step in preparing our data is to split it into three sets: training, test, and validation. This isn't the format of the original data set, so we'll take a small slice of the training data and treat that as our validation set.

```
VALIDATION_SIZE = 5000

validation_data = train_data[:VALIDATION_SIZE, :, :, :]
validation_labels = train_labels[:VALIDATION_SIZE]
train_data = train_data[VALIDATION_SIZE:, :, :, :]
train_labels = train_labels[VALIDATION_SIZE:]

train_size = train_labels.shape[0]

print('Validation shape', validation_data.shape)
print('Train size', train_size)
```

```
Validation shape (5000, 28, 28, 1)
Train size 55000
```

Defining the model

Now that we've prepared our data, we're ready to define our model.

The comments describe the architecture, which fairly typical of models that process image data. The raw input passes through several convolution and max pooling layers with rectified linear activations before several fully connected layers and a softmax loss for predicting the output class. During training, we use dropout.

We'll separate our model definition into three steps:

1. Defining the variables that will hold the trainable weights.
2. Defining the basic model graph structure described above. And,
3. Stamping out several copies of the model graph for training, testing, and validation.

We'll start with the variables.

```
import tensorflow as tf

# We'll bundle groups of examples during training for efficiency.
# This defines the size of the batch.
BATCH_SIZE = 60
# We have only one channel in our grayscale images.

NUM_CHANNELS = 1
# The random seed that defines initialization.
SEED = 42

# This is where training samples and labels are fed to the graph.
# These placeholder nodes will be fed a batch of training data at each
# training step, which we'll write once we define the graph structure.
train_data_node = tf.placeholder(
  tf.float32,
  shape=(BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, NUM_CHANNELS))
train_labels_node = tf.placeholder(tf.float32,
                                   shape=(BATCH_SIZE, NUM_LABELS))

# For the validation and test data, we'll just hold the entire dataset in
# one constant node.
validation_data_node = tf.constant(validation_data)
validation_data_node = tf.constant(validation_data)
test_data_node = tf.constant(test_data)

# The variables below hold all the trainable weights. For each, the
# parameter defines how the variables will be initialized.
conv1_weights = tf.Variable(
  tf.truncated_normal([5, 5, NUM_CHANNELS, 32],  # 5x5 filter, depth 32.
                      stddev=0.1,
                      seed=SEED))
conv1_biases = tf.Variable(tf.zeros([32]))
conv2_weights = tf.Variable(
  tf.truncated_normal([5, 5, 32, 64],
                      stddev=0.1,
                      seed=SEED))
conv2_biases = tf.Variable(tf.constant(0.1, shape=[64]))
fc1_weights = tf.Variable(  # fully connected, depth 512.
  tf.truncated_normal([IMAGE_SIZE // 4 * IMAGE_SIZE // 4 * 64, 512],
                      stddev=0.1,
                      seed=SEED))
fc1_biases = tf.Variable(tf.constant(0.1, shape=[512]))
fc2_weights = tf.Variable(
  tf.truncated_normal([512, NUM_LABELS],
                      stddev=0.1,
                      seed=SEED))
fc2_biases = tf.Variable(tf.constant(0.1, shape=[NUM_LABELS]))

print('Done')
```

```
Done
```

Now that we've defined the variables to be trained, we're ready to wire them together into a TensorFlow graph.

We'll define a helper to do this, `model`, which will return copies of the graph suitable for training and testing. Note the `train` argument, which controls whether or not dropout is used in the hidden layer. (We want to use dropout only during training.)

```
def model(data, train=False):
    """The Model definition."""
```

```
"""The Model definition."""
# 2D convolution, with 'SAME' padding (i.e. the output feature map has
# the same size as the input). Note that {strides} is a 4D array whose
# shape matches the data layout: [image index, y, x, depth].
conv = tf.nn.conv2d(data,
                    conv1_weights,
                    strides=[1, 1, 1, 1],
                    padding='SAME')

# Bias and rectified linear non-linearity.
relu = tf.nn.relu(tf.nn.bias_add(conv, conv1_biases))

# Max pooling. The kernel size spec ksize also follows the layout of
# the data. Here we have a pooling window of 2, and a stride of 2.
pool = tf.nn.max_pool(relu,
                      ksize=[1, 2, 2, 1],
                      strides=[1, 2, 2, 1],
                      padding='SAME')
conv = tf.nn.conv2d(pool,
                    conv2_weights,
                    strides=[1, 1, 1, 1],
                    padding='SAME')
relu = tf.nn.relu(tf.nn.bias_add(conv, conv2_biases))
pool = tf.nn.max_pool(relu,
                      ksize=[1, 2, 2, 1],
                      strides=[1, 2, 2, 1],
                      padding='SAME')

# Reshape the feature map cuboid into a 2D matrix to feed it to the
# fully connected layers.
pool_shape = pool.get_shape().as_list()
reshape = tf.reshape(
    pool,
    [pool_shape[0], pool_shape[1] * pool_shape[2] * pool_shape[3]])

# Fully connected layer. Note that the '+' operation automatically
# broadcasts the biases.
hidden = tf.nn.relu(tf.matmul(reshape, fc1_weights) + fc1_biases)

# Add a 50% dropout during training only. Dropout also scales
# activations such that no rescaling is needed at evaluation time.
```

```
    # activations such that no rescaling is needed at evaluation time.
    if train:
        hidden = tf.nn.dropout(hidden, 0.5, seed=SEED)
    return tf.matmul(hidden, fc2_weights) + fc2_biases

print('Done')
```

```
Done
```

Having defined the basic structure of the graph, we're ready to stamp out multiple copies for training, testing, and validation.

Here, we'll do some customizations depending on which graph we're constructing. `train_prediction` holds the training graph, for which we use cross-entropy loss and weight regularization. We'll adjust the learning rate during training -- that's handled by the `exponential_decay` operation, which is itself an argument to the `MomentumOptimizer` that performs the actual training.

The vaildation and prediction graphs are much simpler the generate -- we need only create copies of the model with the validation and test inputs and a softmax classifier as the output.

```
# Training computation: logits + cross-entropy loss.
logits = model(train_data_node, True)
loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(
  labels=train_labels_node, logits=logits))

# L2 regularization for the fully connected parameters.
regularizers = (tf.nn.l2_loss(fc1_weights) + tf.nn.l2_loss(fc1_biases) +
                tf.nn.l2_loss(fc2_weights) + tf.nn.l2_loss(fc2_biases))
# Add the regularization term to the loss.
loss += 5e-4 * regularizers

# Optimizer: set up a variable that's incremented once per batch and
# controls the learning rate decay.
batch = tf.Variable(0)
# Decay once per epoch, using an exponential schedule starting at 0.01.
learning_rate = tf.train.exponential_decay(
  0.01,                # Base learning rate.
  batch * BATCH_SIZE,  # Current index into the dataset.
  train_size,          # Decay step.
  0.95,                # Decay rate.
  staircase=True)
# Use simple momentum for the optimization.
optimizer = tf.train.MomentumOptimizer(learning_rate,
                                       0.9).minimize(loss,
                                                     global_step=batch)

# Predictions for the minibatch, validation set and test set.
train_prediction = tf.nn.softmax(logits)
# We'll compute them only once in a while by calling their {eval()} method.
validation_prediction = tf.nn.softmax(model(validation_data_node))
test_prediction = tf.nn.softmax(model(test_data_node))

print('Done')
```

```
Done
```

Training and visualizing results

Now that we have the training, test, and validation graphs, we're ready to actually go through the training loop and periodically evaluate loss and error.

All of these operations take place in the context of a session. In Python, we'd write something like:

```
with tf.Session() as s:
  ...training / test / evaluation loop...
```

But, here, we'll want to keep the session open so we can poke at values as we work out the details of training. The TensorFlow API includes a function for this, `InteractiveSession`.

We'll start by creating a session and initializing the varibles we defined above.

```
# Create a new interactive session that we'll use in
# subsequent code cells.
# subsequent code cells.
s = tf.InteractiveSession()

# Use our newly created session as the default for
# subsequent operations.
s.as_default()

# Initialize all the variables we defined above.
tf.global_variables_initializer().run()
```

Now we're ready to perform operations on the graph. Let's start with one round of training. We're going to organize our training steps into batches for efficiency; i.e., training using a small set of examples at each step rather than a single example.

```
BATCH_SIZE = 60

# Grab the first BATCH_SIZE examples and labels.
batch_data = train_data[:BATCH_SIZE, :, :, :]
batch_labels = train_labels[:BATCH_SIZE]

# This dictionary maps the batch data (as a numpy array) to the
# node in the graph it should be fed to.
feed_dict = {train_data_node: batch_data,
             train_labels_node: batch_labels}

# Run the graph and fetch some of the nodes.

_, l, lr, predictions = s.run(
  [optimizer, loss, learning_rate, train_prediction],
  feed_dict=feed_dict)

print('Done')
```

```
Done
```

Let's take a look at the predictions. How did we do? Recall that the output will be probabilities over the possible classes, so let's look at those probabilities.

```
print(predictions[0])
```

```
[  2.25393116e-04   4.76219611e-05   1.66867452e-03   5.67827519e-05
   6.03432178e-01   4.34969068e-02   2.19316553e-05   1.41286102e-04
   1.54903100e-05   3.50893795e-01]
```

As expected without training, the predictions are all noise. Let's write a scoring function that picks the class with the maximum probability and compares with the example's label. We'll start by converting the probability vectors returned by the softmax into predictions we can match against the labels.

```
# The highest probability in the first entry.
print('First prediction', numpy.argmax(predictions[0]))

# But, predictions is actually a list of BATCH_SIZE probability vectors.
print(predictions.shape)

# So, we'll take the highest probability for each vector.
print('All predictions', numpy.argmax(predictions, 1))
```

```
First prediction 4
(60, 10)
All predictions [4 4 2 7 7 7 7 7 7 7 7 7 0 8 9 0 7 7 0 7 4 0 5 0 9 9 7 0 7 4 7
7 7 0 7 7 9
 7 9 9 0 7 7 7 2 7 0 7 2 9 9 9 9 9 0 7 9 4 8 7]
```

Next, we can do the same thing for our labels -- using `argmax` to convert our 1-hot encoding into a digit class.

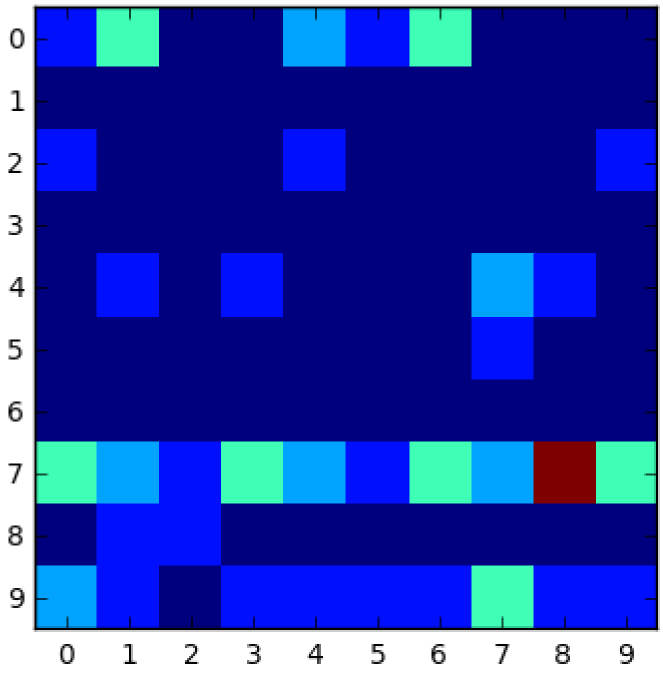
```
print('Batch labels', numpy.argmax(batch_labels, 1))
```

```
Batch labels [7 3 4 6 1 8 1 0 9 8 0 3 1 2 7 0 2 9 6 0 1 6 7 1 9 7 6 5 5 8 8 3 4
4 8 7 3
 6 4 6 6 3 8 8 9 9 4 4 0 7 8 1 0 0 1 8 5 7 1 7]
```

Now we can compare the predicted and label classes to compute the error rate and confusion matrix for this batch.

```
correct = numpy.sum(numpy.argmax(predictions, 1) == numpy.argmax(batch_labels, 1))
total = predictions.shape[0]

print(float(correct) / float(total))

confusions = numpy.zeros([10, 10], numpy.float32)
bundled = zip(numpy.argmax(predictions, 1), numpy.argmax(batch_labels, 1))
for predicted, actual in bundled:
  confusions[predicted, actual] += 1

plt.grid(False)
plt.xticks(numpy.arange(NUM_LABELS))
plt.yticks(numpy.arange(NUM_LABELS))
plt.imshow(confusions, cmap=plt.cm.jet, interpolation='nearest');
```

```
0.06666666666666667
```



Now let's wrap this up into our scoring function.

```
def error_rate(predictions, labels):
    """Return the error rate and confusions."""
    correct = numpy.sum(numpy.argmax(predictions, 1) == numpy.argmax(labels,
1))
    total = predictions.shape[0]

    error = 100.0 - (100 * float(correct) / float(total))

    confusions = numpy.zeros([10, 10], numpy.float32)
    bundled = zip(numpy.argmax(predictions, 1), numpy.argmax(labels, 1))
    for predicted, actual in bundled:
        confusions[predicted, actual] += 1

    return error, confusions

print('Done')
```

```
Done
```

We'll need to train for some time to actually see useful predicted values. Let's define a loop that will go through our data. We'll print the loss and error periodically.

Here, we want to iterate over the entire data set rather than just the first batch, so we'll need to slice the data to that end.

(One pass through our training set will take some time on a CPU, so be patient if you are executing this notebook.)

```
# Train over the first 1/4th of our training set.
steps = train_size // BATCH_SIZE
for step in range(steps):
    # Compute the offset of the current minibatch in the data.
    # Note that we could use better randomization across epochs.
    offset = (step * BATCH_SIZE) % (train_size - BATCH_SIZE)
    batch_data = train_data[offset:(offset + BATCH_SIZE), :, :, :]
    batch_labels = train_labels[offset:(offset + BATCH_SIZE)]
    # This dictionary maps the batch data (as a numpy array) to the
    # node in the graph it should be fed to.
    feed_dict = {train_data_node: batch_data,
                 train_labels_node: batch_labels}
    # Run the graph and fetch some of the nodes.
    _, l, lr, predictions = s.run(
      [optimizer, loss, learning_rate, train_prediction],
      feed_dict=feed_dict)


    # Print out the loss periodically.
    if step % 100 == 0:
        error, _ = error_rate(predictions, batch_labels)
        print('Step %d of %d' % (step, steps))
        print('Mini-batch loss: %.5f Error: %.5f Learning rate: %.5f' % (l,
error, lr))
        print('Validation error: %.1f%%' % error_rate(
              validation_prediction.eval(), validation_labels)[0])
```

```
Step 0 of 916
Mini-batch loss: 7.71249 Error: 91.66667 Learning rate: 0.01000
Validation error: 88.9%
Step 100 of 916
Mini-batch loss: 3.28715 Error: 8.33333 Learning rate: 0.01000
Validation error: 5.8%
Step 200 of 916
Mini-batch loss: 3.30949 Error: 8.33333 Learning rate: 0.01000
Validation error: 3.6%
Step 300 of 916
Mini-batch loss: 3.15385 Error: 3.33333 Learning rate: 0.01000
Validation error: 3.1%
Step 400 of 916
Mini-batch loss: 3.08212 Error: 1.66667 Learning rate: 0.01000
Validation error: 2.7%
Step 500 of 916
Mini-batch loss: 3.02827 Error: 1.66667 Learning rate: 0.01000
Validation error: 2.2%
```

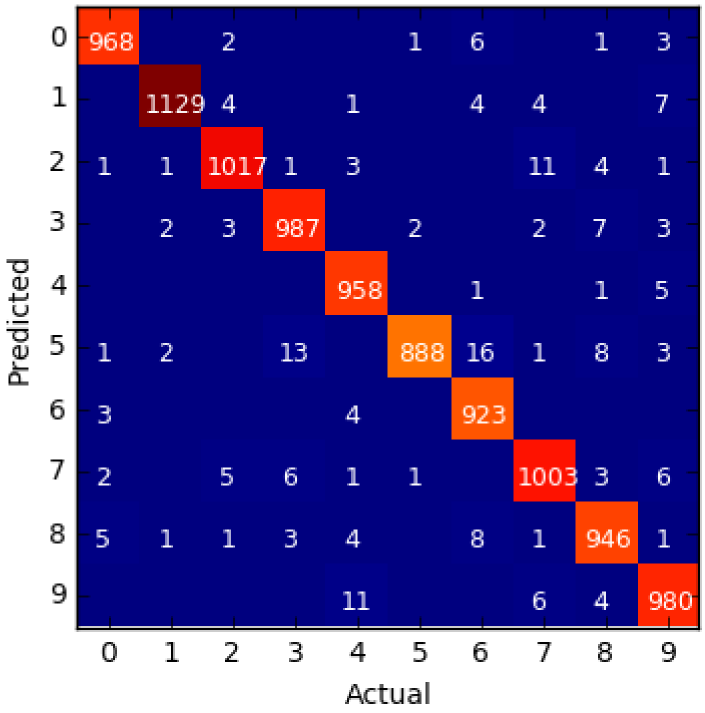
```
Step 600 of 916
Mini-batch loss: 3.03260 Error: 5.00000 Learning rate: 0.01000
Validation error: 1.9%
Step 700 of 916
Mini-batch loss: 3.16032 Error: 6.66667 Learning rate: 0.01000
Validation error: 2.2%
Step 800 of 916
Mini-batch loss: 3.06246 Error: 3.33333 Learning rate: 0.01000
Validation error: 2.0%
Step 900 of 916
Mini-batch loss: 2.85098 Error: 0.00000 Learning rate: 0.01000
Validation error: 1.9%
```

The error seems to have gone down. Let's evaluate the results using the test set.

To help identify rare mispredictions, we'll include the raw count of each (prediction, label) pair in the confusion matrix.

```python
test_error, confusions = error_rate(test_prediction.eval(), test_labels)
print('Test error: %.1f%%' % test_error)

plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.grid(False)
plt.xticks(numpy.arange(NUM_LABELS))
plt.yticks(numpy.arange(NUM_LABELS))
plt.imshow(confusions, cmap=plt.cm.jet, interpolation='nearest');

for i, cas in enumerate(confusions):
    for j, count in enumerate(cas):
        if count > 0:
            xoff = .07 * len(str(count))
            plt.text(j-xoff, i+.2, int(count), fontsize=9, color='white')
```

```
Test error: 2.0%
```

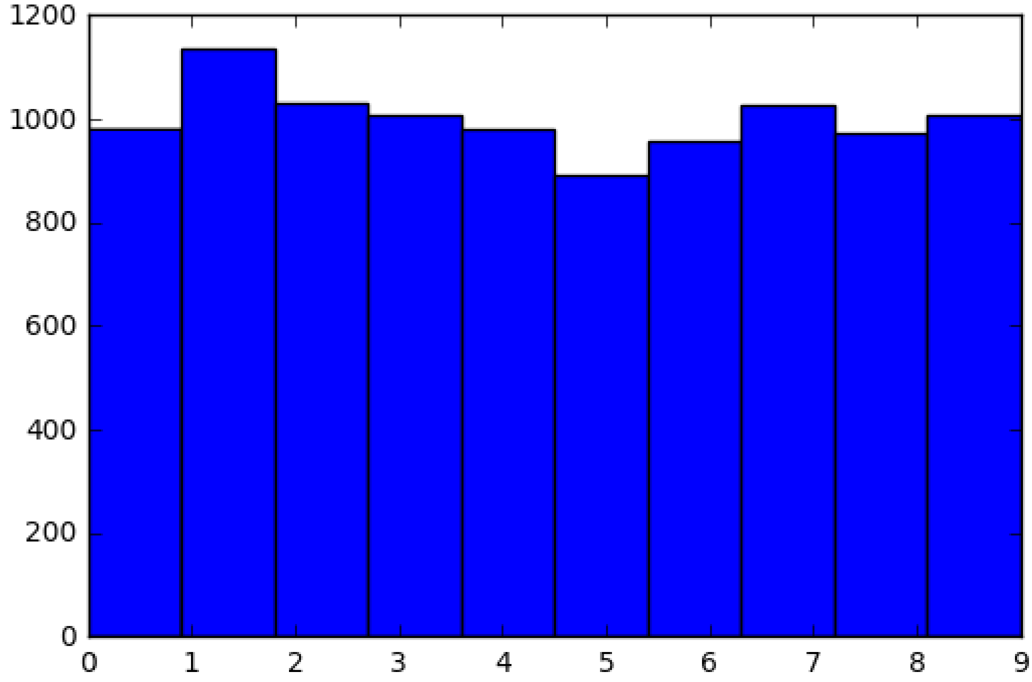


	0	1	2	3	4	5	6	7	8	9
0	968		2			1	6		1	3
1		1129	4		1		4	4		7
2	1	1	1017	1	3			11	4	1
3		2	3	987		2		2	7	3
4					958		1		1	5
5	1	2		13		888	16	1	8	3
6	3				4		923			
7	2		5	6	1	1		1003	3	6
8	5	1	1	3	4		8	1	946	1
9					11			6	4	980

We can see here that we're mostly accurate, with some errors you might expect, e.g., '9' is often confused as '4'.

Let's do another sanity check to make sure this matches roughly the distribution of our test set, e.g., it seems like we have fewer '5' values.

```
plt.xticks(numpy.arange(NUM_LABELS))
plt.hist(numpy.argmax(test_labels, 1));
```



Indeed, we appear to have fewer 5 labels in the test set. So, on the whole, it seems like our model is learning and our early results are sensible.

But, we've only done one round of training. We can greatly improve accuracy by training for longer. To try this out, just re-execute the training cell above.