

Convolutional Neural Network (CNN)

<https://pythonprogramming.net/convnet-model-deep-l>

Data - Deep Learning and Neural Networks with Python and Pytorch

```
import os
```

```
import numpy as np
from tqdm import tqdm
```

```

class DogsVSCats():
    IMG_SIZE = 50
    CATS = "PetImages/Cat"
    DOGS = "PetImages/Dog"
    TESTING = "PetImages/Testing"
    LABELS = {CATS: 0, DOGS: 1}
    training_data = []

    catcount = 0
    dogcount = 0

    def make_training_data(self):
        for label in self.LABELS:
            print(label)
            for f in tqdm(os.listdir(label)):
                if "jpg" in f:
                    try:
                        path = os.path.join(label, f)
                        img = cv2.imread(path, cv2.IMREAD_GRAYSCALE)
                        img = cv2.resize(img, (self.IMG_SIZE, self.IMG_SIZE))
                        # do something like print(np.eye(2)[1]), just makes one_hot
                        self.training_data.append([np.array(img), np.eye(2)[self.LABELS[label]]])
                        #print(np.eye(2)[self.LABELS[label]])

                    if label == self.CATS:
                        self.catcount += 1
                    elif label == self.DOGS:
                        self.dogcount += 1

            except Exception as e:
                pass
                #print(label, f, str(e))

        np.random.shuffle(self.training_data)
        np.save("training_data.npy", self.training_data)
        print('Cats:', dogsvcats.catcount)
        print('Dogs:', dogsvcats.dogcount)

if REBUILD_DATA:
    dogsvcats = DogsVSCats()
    dogsvcats.make_training_data()

training_data = np.load("training_data.npy", allow_pickle=True)
print(len(training_data))

```

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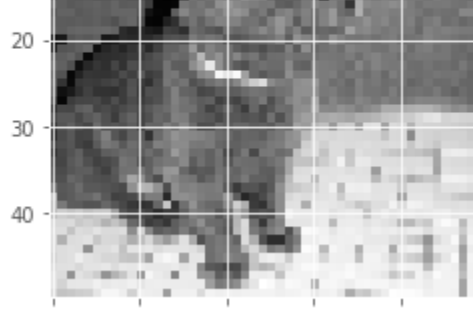
DogsVSCats IMG_SIZE : normalize all of the images by reshaping them to all be the same size CATS = "PetImages/Cat": directory variable DOGS = "PetImages/Dog": directory variable TESTING = "PetImages/Testing": directory variable LABELS = {CATS: 0, DOGS: 1} training_data = []

make_training_data() We read in the data, convert to grayscale, resize the image to whatever we chose, and then append the image data along with the associated class in number form to our training

```
import torch
import matplotlib.pyplot as plt
```

```
Now we can split our training data into X and y, as well as convert it to a tensor:
X = torch.Tensor([i[0] for i in training_data]).view(-1,50,50)
X = X/255.0
y = torch.Tensor([i[1] for i in training_data])
plt.imshow(X[0], cmap="gray")

Out[68]: <matplotlib.image.AxesImage at 0x7fcc9375730>
```



```
In [69]: import torch
import torch.nn as nn
import torch.nn.functional as F

class Net(nn.Module):
    def __init__(self):
        super().__init__() # just run the init of parent class (nn.Module)
        self.conv1 = nn.Conv2d(1, 32, 5) # input is 1 image, 32 output channels, 5x5 kernel / window
        self.conv2 = nn.Conv2d(32, 64, 5) # input is 32, bc the first layer output 32. Then we say the output will be 64 channels, 5x5 kernel / window
```

```

x = torch.randn(50,50).view(-1,1,50,50)
self._to_linear = None
self.convs(x)

self.fc1 = nn.Linear(self._to_linear, 512) #flattening.
self.fc2 = nn.Linear(512, 2) # 512 in, 2 out bc we're doing 2 classes (dog vs cat).

def convs(self, x):
    # max pooling over 2x2
    x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
    x = F.max_pool2d(F.relu(self.conv2(x)), (2, 2))
    x = F.max_pool2d(F.relu(self.conv3(x)), (2, 2))

    if self._to_linear is None:
        self._to_linear = x[0].shape[0]*x[0].shape[1]*x[0].shape[2]
    return x

def forward(self, x):
    x = self.convs(x)
    x = x.view(-1, self._to_linear) # .view is reshape ... this flattens X before
    x = F.relu(self.fc1(x))
    x = self.fc2(x) # bc this is our output layer. No activation here.
    return F.softmax(x, dim=1)

net = Net()
print(net)

Net(
  (conv1): Conv2d(1, 32, kernel_size=(5, 5), stride=(1, 1))
  (conv2): Conv2d(32, 64, kernel_size=(5, 5), stride=(1, 1))
  (conv3): Conv2d(64, 128, kernel_size=(5, 5), stride=(1, 1))
  (fc1): Linear(in_features=512, out_features=512, bias=True)
  (fc2): Linear(in_features=512, out_features=2, bias=True)
)

```

Our Neural Network CNN Net Contains:

nn.Conv2d 2 layers Parameter 1 :: input size number of images Parameter 2 :: output size number of convolutions coming back from image Parameter 3 :: kernel size kernel window size. This is the size of the "window" that you take of pixels. A 5 means we're doing a sliding 5x5 window for convolutions.

nn.Linear 2 layers Parameter 1 :: input size This is 4450 pixel image (1x784) Parameter 2 :: output size Number of output Classes

Random Data To Determine Linear Input Size To determine the actual shape of the flattened output after the first convolutional layers

conv func x :: image representation as a 1xDIM

__max_pool2d activation function__

```
output :: (input data) * weights

__relu activation function__
```

feed-forward func The initial path of the input will just go through our convs method, which we separated out, again, so we could use it in other places.

```
import time
```

```
BATCH_SIZE = 100
EPOCHS = 1
```

```
optimizer = optim.Adam(net.parameters(), lr=0.001)
loss function = nn.MSELoss()
```

```
VAL_PCT = 0.1 # lets reserve 10% of our data for validation
val_size = int(len(X)*VAL_PCT)
```

```
train_X = X[:-val_size]
train_y = y[:-val_size]
```

```
test_X = X[-val_size:]
test_y = y[-val_size:]
```

```
def train(net):
    BATCH_SIZE = 100
```

```
for epoch in range(EPOCHS):
```

```
batch_y = train_y[i:i+BATCH_SIZE]
```

[illegible]

```
loss = loss_function(outputs, batch_y)
```

```
optimizer.step()
print(loss)
```

```
def test(net):
```

```
total = 0
with torch.no_grad():
```

```
net_out = net(test_X[i].view(-1, 1, 50, 50).to(device))[0]
```

```
predicted_class = torch.argmax(net_out)
if predicted_class == real_class:
```

```
total += 1
print("Accuracy:", round(correct/total,3))
```

```
if torch.cuda.is_available():
    device = torch.device("cuda:0") # you can continue going on here.
```

```
else:
    device = torch.device("cpu")
```

```
test_Y_to(device)
```

Running on the CPU

$$\begin{bmatrix} 1., & 0. \end{bmatrix},$$
$$\begin{bmatrix} 1. & 0. \\ 1. & 0. \end{bmatrix}$$

Notes

```
import time

MODEL_NAME = f"model-{int(time.time())}"

def fwd_pass(X, y, train=False):
    if train:
        net.zero_grad()
    outputs = net(X)
    matches = [torch.argmax(i)==torch.argmax(j) for i, j in zip(outputs, y)]
    acc = matches.count(True)/len(matches)
    loss = loss_function(outputs, y)

    if train:
        loss.backward()
        optimizer.step()

    return acc, loss

def train(net):
    BATCH_SIZE = 100
    EPOCHS = 1

    with open("model.log", "a") as f:
        for epoch in range(EPOCHS):
            for i in tqdm(range(0, len(train_X), BATCH_SIZE)):
                batch_X = train_X[i:i+BATCH_SIZE].view(-1,1,50,50)
                batch_y = train_y[i:i+BATCH_SIZE]

                batch_X, batch_y = batch_X.to(device), batch_y.to(device)

                acc, loss = fwd_pass(batch_X, batch_y, train=True)

                #print(f"Acc: {round(float(acc),2)} Loss: {round(float(loss),4)}")
                #f.write(f"{MODEL_NAME},{round(time.time(),3)},train,{round(float(acc),2)},{round(float(loss),4)}\n")
                # just to show the above working, and then get out:
                if i % 10 == 0:
                    val_acc, val_loss = test(size=100)
                    f.write(f"{MODEL_NAME},{round(time.time(),3)},{round(float(acc),2)},{round(float(loss), 4)},{round(float(val_acc),2)},{round(float(val_loss),4)}\n")

def test(size=32):
    X, y = train_X[:size], test_y[:size]
    val_acc, val_loss = fwd_pass(X.view(-1, 1, 50, 50).to(device), y.to(device))
    return val_acc, val_loss

train(net)
```

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We moved repeated code and started logging some visualization

```
import matplotlib.pyplot as plt
from matplotlib import style

style.use("ggplot")

model_name = "model-1659781640" #"model-1570499409" # grab whichever model name you want here. We could also just reference the MODEL_NAME if you're in a notebook still

def create_acc_loss_graph(model_name):
    contents = open("model.log", "r").read().split("\n")
```

```
times = []
accuracies = []
```

```
val_accs = []
val_losses = []

for c in contents:
    if model_name in c:
        name, timestamp, acc, loss, val_acc, val_loss = c.split(",")

        times.append(float(timestamp))
        accuracies.append(float(acc))
        losses.append(float(loss))

        val_accs.append(float(val_acc))
        val_losses.append(float(val_loss))

fig = plt.figure()

ax1 = plt.subplot2grid((2,1), (0,0))
ax2 = plt.subplot2grid((2,1), (1,0), sharex=ax1)

ax1.plot(times, accuracies, label="acc")
ax1.plot(times, val_accs, label="val_acc")
ax1.legend(loc=2)
ax2.plot(times, losses, label="loss")
ax2.plot(times, val_losses, label="val_loss")
plt.show()

create_acc_loss_graph(model_name)
```

The figure consists of two vertically stacked line plots sharing a common x-axis representing time, ranging from 640 to 710. The top plot displays accuracy metrics: 'acc' (red line) and 'val_acc' (blue line). The y-axis for accuracy ranges from 0.4 to 0.6. Both lines show significant fluctuations, with 'acc' generally staying above 0.5 and 'val_acc' fluctuating between 0.45 and 0.55. The bottom plot displays loss metrics: 'loss' (red line) and 'val_loss' (blue line). The y-axis for loss ranges from 0.23 to 0.26. Both lines show fluctuations, with 'loss' generally staying below 0.25 and 'val_loss' fluctuating between 0.24 and 0.255. A legend in the top-left corner of each plot identifies the four data series.