Computer Vision CSCI-GA.2272-001 Assignment 2

Introduction

This assignment is an introduction to using PyTorch for training simple neural net models. Two different datasets will be used:

- MNIST digits [handwritten digits]
- CIFAR-10 [32x32 resolution color images of 10 object classes].

Requirements

You should perform this assignment in PyTorch, modify this ipython notebook

To install PyTorch, follow instructions at http://pytorch.org/ (http://pytorch.org/)

In [1]:
```
from __future__ import print_function
import argparse
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import datasets, transforms, utils
from torch.autograd import Variable
```

In [2]:
```
# options
dataset = 'mnist' # options: 'mnist' | 'cifar10'
batch_size = 64   # input batch size for training
epochs = 10       # number of epochs to train
lr = 0.01        # learning rate
```

Warmup [10%]

It is always good practice to visually inspect your data before trying to train a model, since it lets you check for problems and get a feel for the task at hand.

MNIST is a dataset of 70,000 grayscale hand-written digits (0 through 9). 60,000 of these are training images. 10,000 are a held out test set.

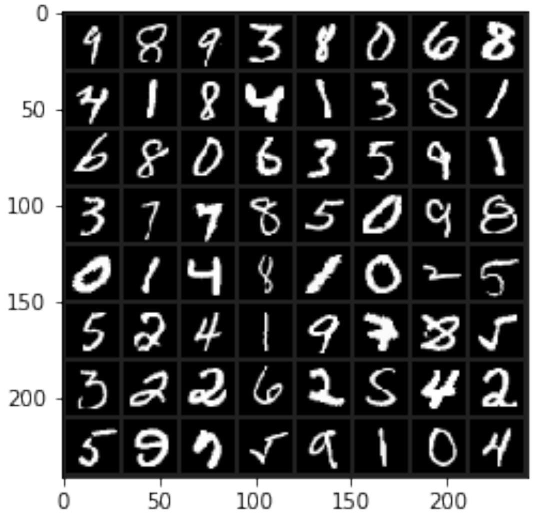
CIFAR-10 is a dataset of 60,000 color images (32 by 32 resolution) across 10 classes (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck). The train/test split is 50k/10k.

Use `matplotlib` and ipython notebook's visualization capabilities to display some of these images. [See this PyTorch tutorial page (http://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html#sphx-glr-beginner-blitz-cifar10-tutorial-py)](http://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html#sphx-glr-beginner-blitz-cifar10-tutorial-py) for hints on how to achieve this.

Relevant Cell: "Data Loading"

In [3]:
```
# Data Loading
# Warning: this cell might take some time when you run it for the f
irst time,
#          because it will download the datasets from the internet
if dataset == 'mnist':
    data_transform = transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.1307,), (0.3081,))
#         transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
    ])
    trainset = datasets.MNIST(root='.', train=True, download=True,
transform=data_transform)
    testset = datasets.MNIST(root='.', train=False, download=True,
transform=data_transform)

elif dataset == 'cifar10':
    data_transform = transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
    ])
    trainset = datasets.CIFAR10(root='.', train=True, download=True
, transform=data_transform)
    testset = datasets.CIFAR10(root='.', train=False, download=True
, transform=data_transform)

train_loader = torch.utils.data.DataLoader(trainset, batch_size=bat
ch_size, shuffle=True, num_workers=0)
test_loader  = torch.utils.data.DataLoader(testset, batch_size=batc
h_size, shuffle=False, num_workers=0)
```

In [4]:
```
%matplotlib inline

import matplotlib.pyplot as plt
import numpy as np

class UnNormalize(object):
    def __init__(self, mean, std):
        self.mean = mean
        self.std = std

    def __call__(self, tensor):
        """
        Args:
            tensor (Tensor): Tensor image of size (C, H, W) to be n
ormalized.
        Returns:
            Tensor: Normalized image.
        """
        for t, m, s in zip(tensor, self.mean, self.std):
            t.mul_(s).add_(m)
            # The normalize code -> t.sub_(m).div_(s)
        return tensor


# Does not work for some unknown (yet to be found) reason
def imshow2(img):
    if dataset =='mnist':
        unorm = UnNormalize(mean=(0.1307,), std=(0.3081,))
    elif dataset == 'cifar10':
        unorm = UnNormalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.
5))

    img = unorm(img)
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()


# functions to show an image
def imshow(img):
    if dataset =='mnist':
        img = img*0.3081 + 0.1307 # unnormalize
    elif dataset == 'cifar10':
        img = img / 2 + 0.5     # unnormalize

    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()


# get some random training images
dataiter = iter(train_loader)
images, labels = dataiter.next()

# show images
imshow(utils.make_grid(images))
```



Training a Single Layer Network on MNIST [20%]

Start by running the training on MNIST. By default if you run this notebook successfully, it will train on MNIST.

This will initialize a single layer model train it on the 50,000 MNIST training images for 10 epochs (passes through the training data).

The loss function cross_entropy (http://pytorch.org/docs/master/nn.html?highlight=cross_entropy#torch.nn.functional.cross_entropy) computes a Logarithm of the Softmax on the output of the neural network, and then computes the negative log-likelihood w.r.t. the given `target`.

The default values for the learning rate, batch size and number of epochs are given in the "options" cell of this notebook. Unless otherwise specified, use the default values throughout this assignment.

Note the decrease in training loss and corresponding decrease in validation errors.

Paste the output into your report.

(a): Add code to plot out the network weights as images (one for each output, of size 28 by 28) after the last epoch. Grab a screenshot of the figure and include it in your report. (Hint threads: #1 (https://discuss.pytorch.org/t/understanding-deep-network-visualize-weights/2060/2?u=smth) #2 (https://github.com/pytorch/vision#utils))

In [5]:
```
## network and optimizer
if dataset == 'mnist':
    num_inputs = 784
elif dataset == 'cifar10':
    num_inputs = 3072

num_outputs = 10 # same for both CIFAR10 and MNIST, both have 10 cl
asses as outputs

class Net(nn.Module):
    def __init__(self, num_inputs, num_outputs):
        super(Net, self).__init__()
        self.linear = nn.Linear(num_inputs, num_outputs)

    def forward(self, input):
        input = input.view(-1, num_inputs) # reshape input to batch
x num_inputs
        output = self.linear(input)
        return output

network = Net(num_inputs, num_outputs)
network.cuda()
optimizer = optim.SGD(network.parameters(), lr=lr)
```

In [6]:
```
def train(epoch):
    network.train()
    loss_collect = []
    for batch_idx, (data, target) in enumerate(train_loader):
        # wrap inputs in Variable
        data, target = Variable(data.cuda()), Variable(target.cuda(
))

        # zero the parameter gradients
        optimizer.zero_grad()

        # forward + backward + optimize
        output = network(data)
        loss = F.cross_entropy(output, target)
        loss.backward()
        optimizer.step()
        loss_collect.append(loss.data[0])

        # print statistics
        if batch_idx % 100 == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'
.format(
                epoch, batch_idx * len(data), len(train_loader.data
set),
                100. * batch_idx / len(train_loader), loss.data[0])
)

    return loss_collect

def test():
    network.eval()
    test_loss = 0
    correct = 0
    for data, target in test_loader:
        data, target = Variable(data.cuda(), volatile=True), Variab
le(target.cuda())
        output = network(data)
        test_loss += F.cross_entropy(output, target, size_average=F
alse).data[0] # sum up batch loss
        pred = output.data.max(1, keepdim=True)[1] # get the index
of the max log-probability
        correct += pred.eq(target.data.view_as(pred)).cpu().sum()

    test_loss /= len(test_loader.dataset)
    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.0f
}%)\n'.format(
        test_loss, correct, len(test_loader.dataset),
        100. * correct / len(test_loader.dataset)))
```

In [7]:
```
loss_g = []
for epoch in range(1, 1 + epochs):
    loss_g.extend(train(epoch))
    test()
```

```
Train Epoch: 1 [0/60000 (0%)]	Loss: 2.432553
Train Epoch: 1 [6400/60000 (11%)]	Loss: 0.830794
```

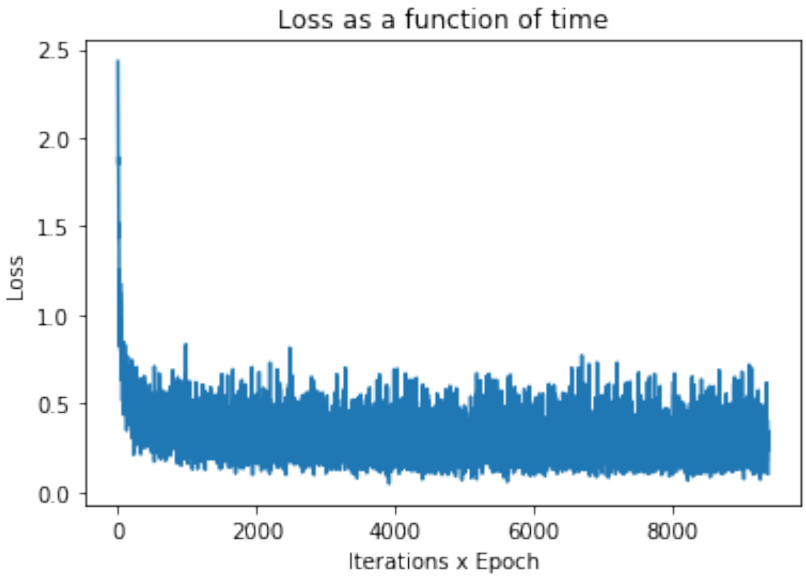
```
Train Epoch: 1 [12800/60000 (21%)]      Loss: 0.524474
Train Epoch: 1 [19200/60000 (32%)]      Loss: 0.263197
Train Epoch: 1 [25600/60000 (43%)]      Loss: 0.561578
Train Epoch: 1 [32000/60000 (53%)]      Loss: 0.516961
Train Epoch: 1 [38400/60000 (64%)]      Loss: 0.279667
Train Epoch: 1 [44800/60000 (75%)]      Loss: 0.286319
Train Epoch: 1 [51200/60000 (85%)]      Loss: 0.241411
Train Epoch: 1 [57600/60000 (96%)]      Loss: 0.233533

Test set: Average loss: 0.3306, Accuracy: 9089/10000 (91%)

Train Epoch: 2 [0/60000 (0%)]   Loss: 0.436318
Train Epoch: 2 [6400/60000 (11%)]       Loss: 0.494924
Train Epoch: 2 [12800/60000 (21%)]      Loss: 0.476951
Train Epoch: 2 [19200/60000 (32%)]      Loss: 0.452447
Train Epoch: 2 [25600/60000 (43%)]      Loss: 0.411289
Train Epoch: 2 [32000/60000 (53%)]      Loss: 0.194206
Train Epoch: 2 [38400/60000 (64%)]      Loss: 0.402748
Train Epoch: 2 [44800/60000 (75%)]      Loss: 0.380579
Train Epoch: 2 [51200/60000 (85%)]      Loss: 0.403462
Train Epoch: 2 [57600/60000 (96%)]      Loss: 0.501765

Test set: Average loss: 0.3029, Accuracy: 9141/10000 (91%)

Train Epoch: 3 [0/60000 (0%)]   Loss: 0.292264
Train Epoch: 3 [6400/60000 (11%)]       Loss: 0.193598
Train Epoch: 3 [12800/60000 (21%)]      Loss: 0.375727
Train Epoch: 3 [19200/60000 (32%)]      Loss: 0.243552
Train Epoch: 3 [25600/60000 (43%)]      Loss: 0.334908
Train Epoch: 3 [32000/60000 (53%)]      Loss: 0.265759
Train Epoch: 3 [38400/60000 (64%)]      Loss: 0.390069
Train Epoch: 3 [44800/60000 (75%)]      Loss: 0.420537
Train Epoch: 3 [51200/60000 (85%)]      Loss: 0.279145
Train Epoch: 3 [57600/60000 (96%)]      Loss: 0.413346

Test set: Average loss: 0.2974, Accuracy: 9165/10000 (92%)

Train Epoch: 4 [0/60000 (0%)]   Loss: 0.631925
Train Epoch: 4 [6400/60000 (11%)]       Loss: 0.188420
Train Epoch: 4 [12800/60000 (21%)]      Loss: 0.332395
Train Epoch: 4 [19200/60000 (32%)]      Loss: 0.293472
Train Epoch: 4 [25600/60000 (43%)]      Loss: 0.275343
Train Epoch: 4 [32000/60000 (53%)]      Loss: 0.384579
Train Epoch: 4 [38400/60000 (64%)]      Loss: 0.200331
Train Epoch: 4 [44800/60000 (75%)]      Loss: 0.281195
Train Epoch: 4 [51200/60000 (85%)]      Loss: 0.403520
Train Epoch: 4 [57600/60000 (96%)]      Loss: 0.386153

Test set: Average loss: 0.2867, Accuracy: 9188/10000 (92%)

Train Epoch: 5 [0/60000 (0%)]   Loss: 0.229332
Train Epoch: 5 [6400/60000 (11%)]       Loss: 0.355931
Train Epoch: 5 [12800/60000 (21%)]      Loss: 0.220135
Train Epoch: 5 [19200/60000 (32%)]      Loss: 0.265769
Train Epoch: 5 [25600/60000 (43%)]      Loss: 0.371632
Train Epoch: 5 [32000/60000 (53%)]      Loss: 0.473440
Train Epoch: 5 [38400/60000 (64%)]      Loss: 0.224874
```

```
Train Epoch: 5 [44800/60000 (75%)]	Loss: 0.168951
Train Epoch: 5 [51200/60000 (85%)]	Loss: 0.140584
Train Epoch: 5 [57600/60000 (96%)]	Loss: 0.438026

Test set: Average loss: 0.2842, Accuracy: 9198/10000 (92%)

Train Epoch: 6 [0/60000 (0%)]	Loss: 0.235925
Train Epoch: 6 [6400/60000 (11%)]	Loss: 0.184482
Train Epoch: 6 [12800/60000 (21%)]	Loss: 0.232548
Train Epoch: 6 [19200/60000 (32%)]	Loss: 0.148201
Train Epoch: 6 [25600/60000 (43%)]	Loss: 0.135537
Train Epoch: 6 [32000/60000 (53%)]	Loss: 0.306238
Train Epoch: 6 [38400/60000 (64%)]	Loss: 0.247220
Train Epoch: 6 [44800/60000 (75%)]	Loss: 0.412690
Train Epoch: 6 [51200/60000 (85%)]	Loss: 0.286281
Train Epoch: 6 [57600/60000 (96%)]	Loss: 0.187953

Test set: Average loss: 0.2819, Accuracy: 9213/10000 (92%)

Train Epoch: 7 [0/60000 (0%)]	Loss: 0.215312
Train Epoch: 7 [6400/60000 (11%)]	Loss: 0.164351
Train Epoch: 7 [12800/60000 (21%)]	Loss: 0.222654
Train Epoch: 7 [19200/60000 (32%)]	Loss: 0.416943
Train Epoch: 7 [25600/60000 (43%)]	Loss: 0.121763
Train Epoch: 7 [32000/60000 (53%)]	Loss: 0.147365
Train Epoch: 7 [38400/60000 (64%)]	Loss: 0.351305
Train Epoch: 7 [44800/60000 (75%)]	Loss: 0.373331
Train Epoch: 7 [51200/60000 (85%)]	Loss: 0.400591
Train Epoch: 7 [57600/60000 (96%)]	Loss: 0.196848

Test set: Average loss: 0.2786, Accuracy: 9225/10000 (92%)

Train Epoch: 8 [0/60000 (0%)]	Loss: 0.296293
Train Epoch: 8 [6400/60000 (11%)]	Loss: 0.629407
Train Epoch: 8 [12800/60000 (21%)]	Loss: 0.157068
Train Epoch: 8 [19200/60000 (32%)]	Loss: 0.124238
Train Epoch: 8 [25600/60000 (43%)]	Loss: 0.494769
Train Epoch: 8 [32000/60000 (53%)]	Loss: 0.183174
Train Epoch: 8 [38400/60000 (64%)]	Loss: 0.290588
Train Epoch: 8 [44800/60000 (75%)]	Loss: 0.218211
Train Epoch: 8 [51200/60000 (85%)]	Loss: 0.203376
Train Epoch: 8 [57600/60000 (96%)]	Loss: 0.347856

Test set: Average loss: 0.2780, Accuracy: 9206/10000 (92%)

Train Epoch: 9 [0/60000 (0%)]	Loss: 0.294717
Train Epoch: 9 [6400/60000 (11%)]	Loss: 0.240345
Train Epoch: 9 [12800/60000 (21%)]	Loss: 0.240508
Train Epoch: 9 [19200/60000 (32%)]	Loss: 0.254494
Train Epoch: 9 [25600/60000 (43%)]	Loss: 0.152996
Train Epoch: 9 [32000/60000 (53%)]	Loss: 0.227247
Train Epoch: 9 [38400/60000 (64%)]	Loss: 0.204751
Train Epoch: 9 [44800/60000 (75%)]	Loss: 0.318234
Train Epoch: 9 [51200/60000 (85%)]	Loss: 0.164535
Train Epoch: 9 [57600/60000 (96%)]	Loss: 0.195484

Test set: Average loss: 0.2772, Accuracy: 9209/10000 (92%)
```

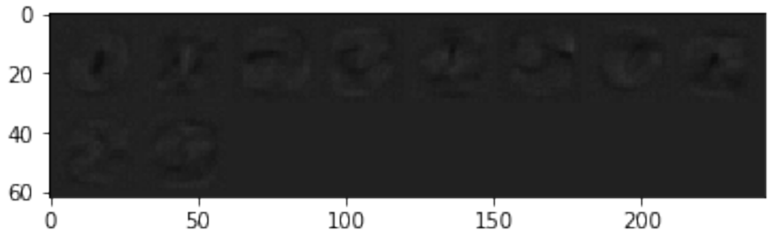
```
Train Epoch: 10 [0/60000 (0%)]  Loss: 0.365687
Train Epoch: 10 [6400/60000 (11%)]      Loss: 0.263153
Train Epoch: 10 [12800/60000 (21%)]     Loss: 0.263110
Train Epoch: 10 [19200/60000 (32%)]     Loss: 0.184863
Train Epoch: 10 [25600/60000 (43%)]     Loss: 0.199894
Train Epoch: 10 [32000/60000 (53%)]     Loss: 0.274847
Train Epoch: 10 [38400/60000 (64%)]     Loss: 0.309169
Train Epoch: 10 [44800/60000 (75%)]     Loss: 0.258047
Train Epoch: 10 [51200/60000 (85%)]     Loss: 0.100652
Train Epoch: 10 [57600/60000 (96%)]     Loss: 0.275231

Test set: Average loss: 0.2759, Accuracy: 9217/10000 (92%)
```

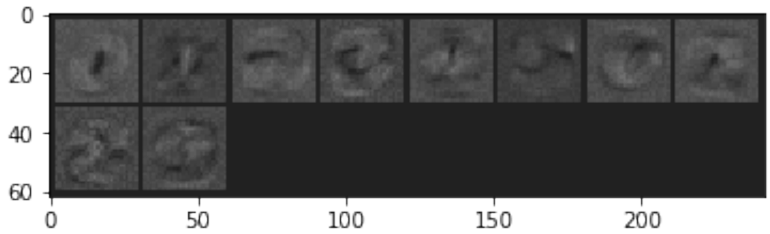
In [8]:
```
plt.plot(loss_g)
plt.xlabel("Iterations x Epoch")
plt.ylabel("Loss")
plt.title("Loss as a function of time")
```

Out[8]:
```
<matplotlib.text.Text at 0x7faa3008ddd8>
```



```
In [9]: for x in network.modules():
            if isinstance(x, nn.Linear):
                imshow(utils.make_grid(x.weight.data.cpu().view(10,1,28,28)
))
                imshow(utils.make_grid(x.weight.data.cpu().view(10,1,28,28)
,normalize=True, scale_each=True))
```





(b): Reduce the number of training examples to just 50. [Hint: limit the iterator in the `train` function]. Paste the output into your report and explain what is happening to the model.

```
In [10]: from torch.utils.data.sampler import Sampler

class SubsetSampler(Sampler):
    """Samples elements sequentially, always in the same order.
    Arguments:
        data_source (Dataset): dataset to sample from
        num_samples (int): number of samples to draw
    """

    def __init__(self, data_source, num_samples):
        self.data_source = data_source
        if num_samples < len(self.data_source):
            self.num_samples = num_samples
        else:
            self.num_samples = len(self.data_source)

    def __iter__(self):
        return iter(range(self.num_samples))

    def __len__(self):
        return self.num_samples
```

In [11]:

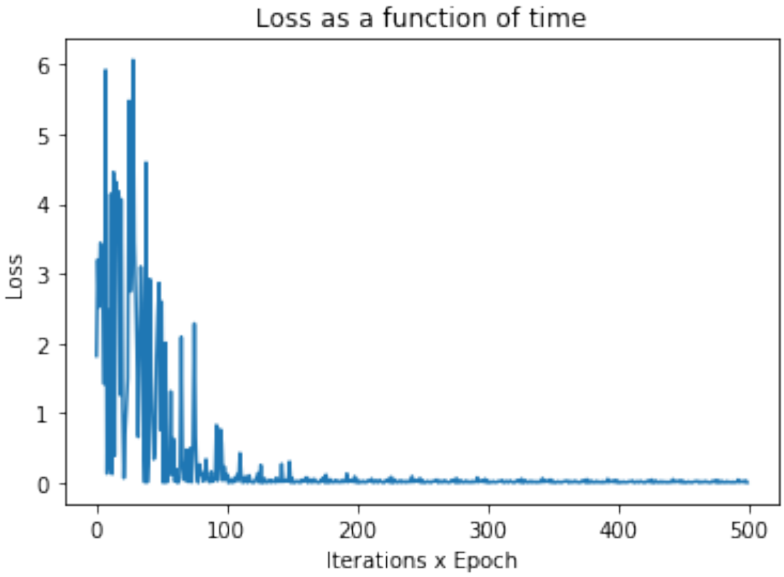
```
subset_sampler = SubsetSampler(trainset, 50)
train_loader = torch.utils.data.DataLoader(trainset, batch_size=1, shuffle=False, sampler=subset_sampler, num_workers=0)
subset_sampler = SubsetSampler(testset, 50)
test_loader  = torch.utils.data.DataLoader(testset, batch_size=1, shuffle=False, sampler=subset_sampler, num_workers=0)

network = Net(num_inputs, num_outputs)
network.cuda()
optimizer = optim.SGD(network.parameters(), lr=lr)
```

In [12]:
```python
loss_g = []
for epoch in range(1, 1 + epochs):
    loss_g.extend(train(epoch))
    test()
```

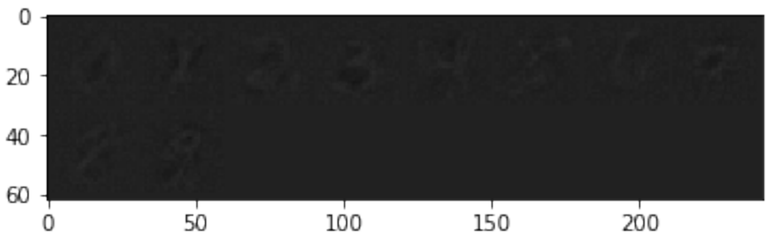
```
Train Epoch: 1 [0/60000 (0%)]   Loss: 1.818081

Test set: Average loss: 0.0073, Accuracy: 27/10000 (0%)

Train Epoch: 2 [0/60000 (0%)]   Loss: 2.596171

Test set: Average loss: 0.0058, Accuracy: 32/10000 (0%)

Train Epoch: 3 [0/60000 (0%)]   Loss: 0.123463

Test set: Average loss: 0.0053, Accuracy: 34/10000 (0%)

Train Epoch: 4 [0/60000 (0%)]   Loss: 0.063994

Test set: Average loss: 0.0052, Accuracy: 36/10000 (0%)

Train Epoch: 5 [0/60000 (0%)]   Loss: 0.044397

Test set: Average loss: 0.0052, Accuracy: 36/10000 (0%)

Train Epoch: 6 [0/60000 (0%)]   Loss: 0.036086

Test set: Average loss: 0.0051, Accuracy: 36/10000 (0%)

Train Epoch: 7 [0/60000 (0%)]   Loss: 0.030964

Test set: Average loss: 0.0051, Accuracy: 36/10000 (0%)

Train Epoch: 8 [0/60000 (0%)]   Loss: 0.027339

Test set: Average loss: 0.0051, Accuracy: 36/10000 (0%)

Train Epoch: 9 [0/60000 (0%)]   Loss: 0.024580

Test set: Average loss: 0.0051, Accuracy: 36/10000 (0%)

Train Epoch: 10 [0/60000 (0%)]  Loss: 0.022384

Test set: Average loss: 0.0051, Accuracy: 36/10000 (0%)
```

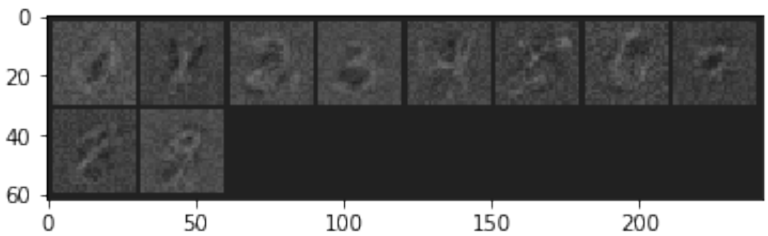
In [13]:
```
plt.plot(loss_g)
plt.xlabel("Iterations x Epoch")
plt.ylabel("Loss")
plt.title("Loss as a function of time")
```

Out[13]:
```
<matplotlib.text.Text at 0x7faa301bf710>
```



In [14]:
```
for x in network.modules():
    if isinstance(x, nn.Linear):
        imshow(utils.make_grid(x.weight.data.cpu().view(10,1,28,28)
))
        imshow(utils.make_grid(x.weight.data.cpu().view(10,1,28,28)
,normalize=True, scale_each=True))
```





Overfit

As we can see the loss (indicator of training error) quickly becomes very small (tending to 0) while the test error (as training accuracy tends to 0) becomes very high. These are clear indicators of overfitting the data. Since a very small amount of data was provided, the model overfits over it and lacks the ability to generalise at all which leads to very poor test accuracy.

By definition, **overfitting is a modeling error which occurs when a function is too closely fit to a limited set of data points** which is clearly what happens in this case. Overfitting the model generally takes the form of making an overly complex model to explain idiosyncrasies in the data under study. There are many ways to fight overfitting such as the following (not an exhaustive list by any means):

- Get more data (and/or use data augmentation)
- Use regularization, like Dropout and perhaps even L1 and L2
- Feature scale clipping
- Global average pooling
- Make network smaller
- Early stopping

Training a Multi-Layer Network on MNIST [20%]

- Add an extra layer to the network with 1000 hidden units and a `tanh` non-linearity. [Hint: modify the `Net` class]. Train the model for 10 epochs and save the output into your report.

In [15]:
```
train_loader = torch.utils.data.DataLoader(trainset, batch_size=bat
ch_size, shuffle=True, num_workers=0)
test_loader  = torch.utils.data.DataLoader(testset, batch_size=batc
h_size, shuffle=False, num_workers=0)

class Net(nn.Module):
    def __init__(self, num_inputs, num_outputs, hidden_units):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(num_inputs, hidden_units)
        self.fc2 = nn.Linear(hidden_units, num_outputs)

    def forward(self, x):
        x = x.view(-1, num_inputs) # reshape input to batch x num_i
nputs
        x = self.fc1(x)
        x = F.tanh(x)
        x = self.fc2(x)
        return x

network = Net(num_inputs, num_outputs, hidden_units=1000)
network.cuda()
optimizer = optim.SGD(network.parameters(), lr=lr)
```

In [16]:
```
loss_g = []
for epoch in range(1, 1 + epochs):
    loss_g.extend(train(epoch))
    test()
```

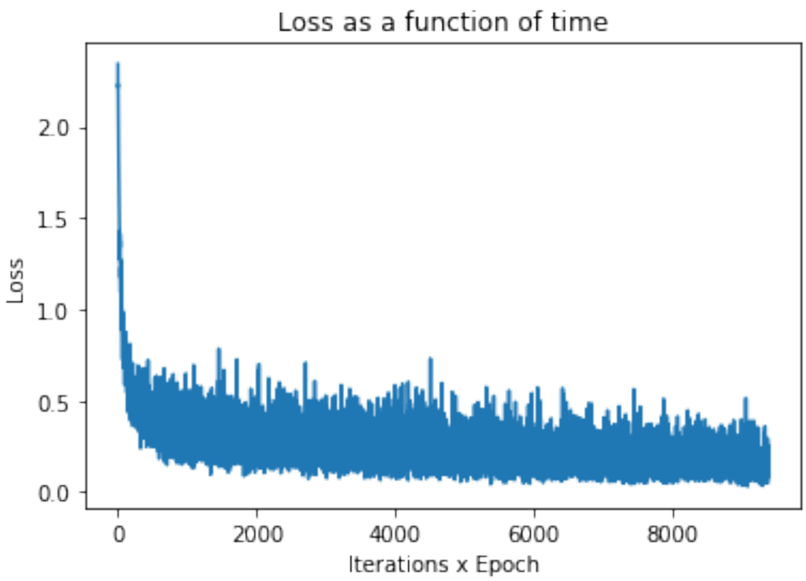
```
Train Epoch: 1 [0/60000 (0%)]	Loss: 2.344141
Train Epoch: 1 [6400/60000 (11%)]	Loss: 0.829380
Train Epoch: 1 [12800/60000 (21%)]	Loss: 0.549929
Train Epoch: 1 [19200/60000 (32%)]	Loss: 0.466398
Train Epoch: 1 [25600/60000 (43%)]	Loss: 0.401492
Train Epoch: 1 [32000/60000 (53%)]	Loss: 0.534058
Train Epoch: 1 [38400/60000 (64%)]	Loss: 0.398345
Train Epoch: 1 [44800/60000 (75%)]	Loss: 0.492511
Train Epoch: 1 [51200/60000 (85%)]	Loss: 0.323353
Train Epoch: 1 [57600/60000 (96%)]	Loss: 0.269988

Test set: Average loss: 0.3233, Accuracy: 9093/10000 (91%)

Train Epoch: 2 [0/60000 (0%)]	Loss: 0.435899
Train Epoch: 2 [6400/60000 (11%)]	Loss: 0.262041
Train Epoch: 2 [12800/60000 (21%)]	Loss: 0.361291
Train Epoch: 2 [19200/60000 (32%)]	Loss: 0.300726
Train Epoch: 2 [25600/60000 (43%)]	Loss: 0.453793
Train Epoch: 2 [32000/60000 (53%)]	Loss: 0.260048
Train Epoch: 2 [38400/60000 (64%)]	Loss: 0.406989
Train Epoch: 2 [44800/60000 (75%)]	Loss: 0.527357
Train Epoch: 2 [51200/60000 (85%)]	Loss: 0.375693
Train Epoch: 2 [57600/60000 (96%)]	Loss: 0.284525

Test set: Average loss: 0.2813, Accuracy: 9203/10000 (92%)

Train Epoch: 3 [0/60000 (0%)]	Loss: 0.359545
Train Epoch: 3 [6400/60000 (11%)]	Loss: 0.326413
Train Epoch: 3 [12800/60000 (21%)]	Loss: 0.268522
Train Epoch: 3 [19200/60000 (32%)]	Loss: 0.431381
Train Epoch: 3 [25600/60000 (43%)]	Loss: 0.345010
Train Epoch: 3 [32000/60000 (53%)]	Loss: 0.291767
Train Epoch: 3 [38400/60000 (64%)]	Loss: 0.346270
Train Epoch: 3 [44800/60000 (75%)]	Loss: 0.274078
Train Epoch: 3 [51200/60000 (85%)]	Loss: 0.234189
Train Epoch: 3 [57600/60000 (96%)]	Loss: 0.210701

Test set: Average loss: 0.2619, Accuracy: 9249/10000 (92%)

Train Epoch: 4 [0/60000 (0%)]	Loss: 0.192107
Train Epoch: 4 [6400/60000 (11%)]	Loss: 0.449517
Train Epoch: 4 [12800/60000 (21%)]	Loss: 0.199383
Train Epoch: 4 [19200/60000 (32%)]	Loss: 0.148907
Train Epoch: 4 [25600/60000 (43%)]	Loss: 0.310162
Train Epoch: 4 [32000/60000 (53%)]	Loss: 0.230240
Train Epoch: 4 [38400/60000 (64%)]	Loss: 0.524172
Train Epoch: 4 [44800/60000 (75%)]	Loss: 0.323336
Train Epoch: 4 [51200/60000 (85%)]	Loss: 0.183699
Train Epoch: 4 [57600/60000 (96%)]	Loss: 0.179159

Test set: Average loss: 0.2419, Accuracy: 9318/10000 (93%)
```

```
Train Epoch: 5 [0/60000 (0%)]	Loss: 0.305542
Train Epoch: 5 [6400/60000 (11%)]	Loss: 0.322803
Train Epoch: 5 [12800/60000 (21%)]	Loss: 0.099001
Train Epoch: 5 [19200/60000 (32%)]	Loss: 0.143986
Train Epoch: 5 [25600/60000 (43%)]	Loss: 0.172746
Train Epoch: 5 [32000/60000 (53%)]	Loss: 0.277479
Train Epoch: 5 [38400/60000 (64%)]	Loss: 0.230550
Train Epoch: 5 [44800/60000 (75%)]	Loss: 0.179540
Train Epoch: 5 [51200/60000 (85%)]	Loss: 0.131457
Train Epoch: 5 [57600/60000 (96%)]	Loss: 0.210643

Test set: Average loss: 0.2292, Accuracy: 9343/10000 (93%)

Train Epoch: 6 [0/60000 (0%)]	Loss: 0.152416
Train Epoch: 6 [6400/60000 (11%)]	Loss: 0.132874
Train Epoch: 6 [12800/60000 (21%)]	Loss: 0.150181
Train Epoch: 6 [19200/60000 (32%)]	Loss: 0.122614
Train Epoch: 6 [25600/60000 (43%)]	Loss: 0.191909
Train Epoch: 6 [32000/60000 (53%)]	Loss: 0.221607
Train Epoch: 6 [38400/60000 (64%)]	Loss: 0.286850
Train Epoch: 6 [44800/60000 (75%)]	Loss: 0.199715
Train Epoch: 6 [51200/60000 (85%)]	Loss: 0.143983
Train Epoch: 6 [57600/60000 (96%)]	Loss: 0.222106

Test set: Average loss: 0.2131, Accuracy: 9389/10000 (94%)

Train Epoch: 7 [0/60000 (0%)]	Loss: 0.156749
Train Epoch: 7 [6400/60000 (11%)]	Loss: 0.149103
Train Epoch: 7 [12800/60000 (21%)]	Loss: 0.147713
Train Epoch: 7 [19200/60000 (32%)]	Loss: 0.236170
Train Epoch: 7 [25600/60000 (43%)]	Loss: 0.258319
Train Epoch: 7 [32000/60000 (53%)]	Loss: 0.206529
Train Epoch: 7 [38400/60000 (64%)]	Loss: 0.212687
Train Epoch: 7 [44800/60000 (75%)]	Loss: 0.198772
Train Epoch: 7 [51200/60000 (85%)]	Loss: 0.257168
Train Epoch: 7 [57600/60000 (96%)]	Loss: 0.145119

Test set: Average loss: 0.1977, Accuracy: 9435/10000 (94%)

Train Epoch: 8 [0/60000 (0%)]	Loss: 0.169365
Train Epoch: 8 [6400/60000 (11%)]	Loss: 0.118794
Train Epoch: 8 [12800/60000 (21%)]	Loss: 0.168974
Train Epoch: 8 [19200/60000 (32%)]	Loss: 0.087987
Train Epoch: 8 [25600/60000 (43%)]	Loss: 0.124883
Train Epoch: 8 [32000/60000 (53%)]	Loss: 0.138366
Train Epoch: 8 [38400/60000 (64%)]	Loss: 0.057039
Train Epoch: 8 [44800/60000 (75%)]	Loss: 0.099621
Train Epoch: 8 [51200/60000 (85%)]	Loss: 0.055291
Train Epoch: 8 [57600/60000 (96%)]	Loss: 0.089533

Test set: Average loss: 0.1876, Accuracy: 9466/10000 (95%)

Train Epoch: 9 [0/60000 (0%)]	Loss: 0.124728
Train Epoch: 9 [6400/60000 (11%)]	Loss: 0.228127
Train Epoch: 9 [12800/60000 (21%)]	Loss: 0.278833
Train Epoch: 9 [19200/60000 (32%)]	Loss: 0.133893
Train Epoch: 9 [25600/60000 (43%)]	Loss: 0.203673
```

```
Train Epoch: 9 [32000/60000 (53%)]      Loss: 0.151205
Train Epoch: 9 [38400/60000 (64%)]      Loss: 0.233931
Train Epoch: 9 [44800/60000 (75%)]      Loss: 0.270383
Train Epoch: 9 [51200/60000 (85%)]      Loss: 0.123984
Train Epoch: 9 [57600/60000 (96%)]      Loss: 0.243015

Test set: Average loss: 0.1731, Accuracy: 9502/10000 (95%)

Train Epoch: 10 [0/60000 (0%)]  Loss: 0.107806
Train Epoch: 10 [6400/60000 (11%)]      Loss: 0.122718
Train Epoch: 10 [12800/60000 (21%)]     Loss: 0.060518
Train Epoch: 10 [19200/60000 (32%)]     Loss: 0.131182
Train Epoch: 10 [25600/60000 (43%)]     Loss: 0.051315
Train Epoch: 10 [32000/60000 (53%)]     Loss: 0.076039
Train Epoch: 10 [38400/60000 (64%)]     Loss: 0.221091
Train Epoch: 10 [44800/60000 (75%)]     Loss: 0.085397
Train Epoch: 10 [51200/60000 (85%)]     Loss: 0.206541
Train Epoch: 10 [57600/60000 (96%)]     Loss: 0.190997

Test set: Average loss: 0.1630, Accuracy: 9533/10000 (95%)
```

In [17]:
```
plt.plot(loss_g)
plt.xlabel("Iterations x Epoch")
plt.ylabel("Loss")
plt.title("Loss as a function of time")
```

Out[17]: <matplotlib.text.Text at 0x7faa146885f8>



- Now set the learning rate to 10 and observe what happens during training. Save the output in your report and give a brief explanation

In [18]:
```
train_loader = torch.utils.data.DataLoader(trainset, batch_size=bat
ch_size, shuffle=True, num_workers=0)
test_loader  = torch.utils.data.DataLoader(testset, batch_size=batc
h_size, shuffle=False, num_workers=0)

class Net(nn.Module):
    def __init__(self, num_inputs, num_outputs, hidden_units):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(num_inputs, hidden_units)
        self.fc2 = nn.Linear(hidden_units, num_outputs)

    def forward(self, x):
        x = x.view(-1, num_inputs) # reshape input to batch x num_i
nputs
        x = self.fc1(x)
        x = F.tanh(x)
        x = self.fc2(x)
        return x

network = Net(num_inputs, num_outputs, hidden_units=1000)
network.cuda()
optimizer = optim.SGD(network.parameters(), lr=10)
```

In [19]:
```
loss_g = []
for epoch in range(1, 1 + epochs):
    loss_g.extend(train(epoch))
    test()
```

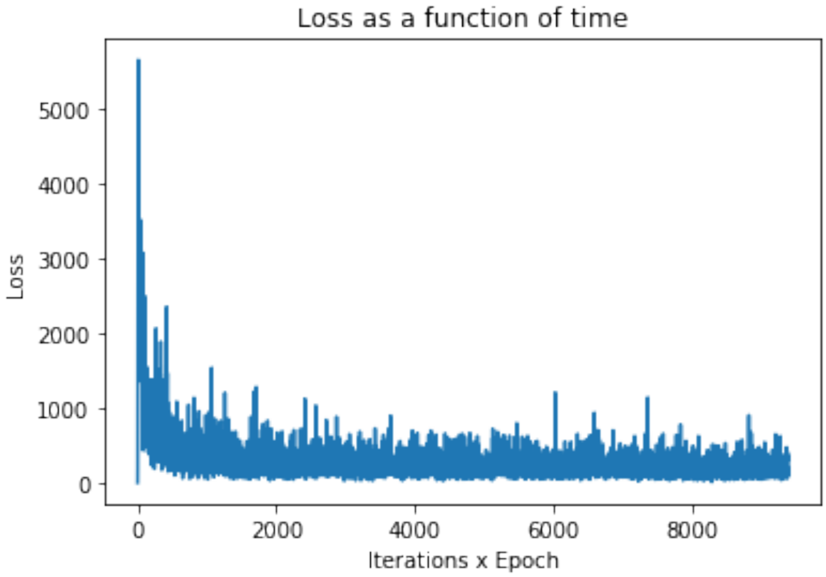
```
Train Epoch: 1 [0/60000 (0%)]	Loss: 2.264647
Train Epoch: 1 [6400/60000 (11%)]	Loss: 1552.625854
Train Epoch: 1 [12800/60000 (21%)]	Loss: 429.011383
Train Epoch: 1 [19200/60000 (32%)]	Loss: 653.251892
Train Epoch: 1 [25600/60000 (43%)]	Loss: 750.171326
Train Epoch: 1 [32000/60000 (53%)]	Loss: 303.090851
Train Epoch: 1 [38400/60000 (64%)]	Loss: 251.620911
Train Epoch: 1 [44800/60000 (75%)]	Loss: 356.836029
Train Epoch: 1 [51200/60000 (85%)]	Loss: 377.940063
Train Epoch: 1 [57600/60000 (96%)]	Loss: 365.819000

Test set: Average loss: 363.3634, Accuracy: 5395/10000 (54%)

Train Epoch: 2 [0/60000 (0%)]	Loss: 300.932678
Train Epoch: 2 [6400/60000 (11%)]	Loss: 564.763000
Train Epoch: 2 [12800/60000 (21%)]	Loss: 241.000412
Train Epoch: 2 [19200/60000 (32%)]	Loss: 152.962906
Train Epoch: 2 [25600/60000 (43%)]	Loss: 173.837845
Train Epoch: 2 [32000/60000 (53%)]	Loss: 98.620087
Train Epoch: 2 [38400/60000 (64%)]	Loss: 228.648590
Train Epoch: 2 [44800/60000 (75%)]	Loss: 425.462982
Train Epoch: 2 [51200/60000 (85%)]	Loss: 582.802124
Train Epoch: 2 [57600/60000 (96%)]	Loss: 333.972961

Test set: Average loss: 386.5838, Accuracy: 5284/10000 (53%)

Train Epoch: 3 [0/60000 (0%)]	Loss: 438.458282
Train Epoch: 3 [6400/60000 (11%)]	Loss: 136.504471
```

```
Train Epoch: 3 [12800/60000 (21%)]      Loss: 288.777313
Train Epoch: 3 [19200/60000 (32%)]      Loss: 317.421295
Train Epoch: 3 [25600/60000 (43%)]      Loss: 454.274750
Train Epoch: 3 [32000/60000 (53%)]      Loss: 526.408508
Train Epoch: 3 [38400/60000 (64%)]      Loss: 241.444458
Train Epoch: 3 [44800/60000 (75%)]      Loss: 137.116394
Train Epoch: 3 [51200/60000 (85%)]      Loss: 427.970093
Train Epoch: 3 [57600/60000 (96%)]      Loss: 285.600677

Test set: Average loss: 355.9410, Accuracy: 5020/10000 (50%)

Train Epoch: 4 [0/60000 (0%)]   Loss: 297.969696
Train Epoch: 4 [6400/60000 (11%)]       Loss: 323.365295
Train Epoch: 4 [12800/60000 (21%)]      Loss: 308.344421
Train Epoch: 4 [19200/60000 (32%)]      Loss: 364.809753
Train Epoch: 4 [25600/60000 (43%)]      Loss: 100.907837
Train Epoch: 4 [32000/60000 (53%)]      Loss: 94.421906
Train Epoch: 4 [38400/60000 (64%)]      Loss: 115.261230
Train Epoch: 4 [44800/60000 (75%)]      Loss: 297.078430
Train Epoch: 4 [51200/60000 (85%)]      Loss: 417.447998
Train Epoch: 4 [57600/60000 (96%)]      Loss: 134.018051

Test set: Average loss: 398.5276, Accuracy: 5355/10000 (54%)

Train Epoch: 5 [0/60000 (0%)]   Loss: 373.431091
Train Epoch: 5 [6400/60000 (11%)]       Loss: 216.246796
Train Epoch: 5 [12800/60000 (21%)]      Loss: 158.145477
Train Epoch: 5 [19200/60000 (32%)]      Loss: 390.546051
Train Epoch: 5 [25600/60000 (43%)]      Loss: 131.778931
Train Epoch: 5 [32000/60000 (53%)]      Loss: 264.217712
Train Epoch: 5 [38400/60000 (64%)]      Loss: 311.592957
Train Epoch: 5 [44800/60000 (75%)]      Loss: 116.125450
Train Epoch: 5 [51200/60000 (85%)]      Loss: 583.161194
Train Epoch: 5 [57600/60000 (96%)]      Loss: 135.884491

Test set: Average loss: 154.0317, Accuracy: 7044/10000 (70%)

Train Epoch: 6 [0/60000 (0%)]   Loss: 239.725189
Train Epoch: 6 [6400/60000 (11%)]       Loss: 378.847046
Train Epoch: 6 [12800/60000 (21%)]      Loss: 264.241699
Train Epoch: 6 [19200/60000 (32%)]      Loss: 223.253784
Train Epoch: 6 [25600/60000 (43%)]      Loss: 160.195160
Train Epoch: 6 [32000/60000 (53%)]      Loss: 273.797913
Train Epoch: 6 [38400/60000 (64%)]      Loss: 237.564438
Train Epoch: 6 [44800/60000 (75%)]      Loss: 103.915703
Train Epoch: 6 [51200/60000 (85%)]      Loss: 144.754944
Train Epoch: 6 [57600/60000 (96%)]      Loss: 110.838966

Test set: Average loss: 520.0282, Accuracy: 5722/10000 (57%)

Train Epoch: 7 [0/60000 (0%)]   Loss: 397.853577
Train Epoch: 7 [6400/60000 (11%)]       Loss: 141.418396
Train Epoch: 7 [12800/60000 (21%)]      Loss: 76.453957
Train Epoch: 7 [19200/60000 (32%)]      Loss: 117.712090
Train Epoch: 7 [25600/60000 (43%)]      Loss: 182.777176
Train Epoch: 7 [32000/60000 (53%)]      Loss: 128.429596
Train Epoch: 7 [38400/60000 (64%)]      Loss: 166.386932
```

```
Train Epoch: 7 [44800/60000 (75%)]      Loss: 214.965927
Train Epoch: 7 [51200/60000 (85%)]      Loss: 226.164246
Train Epoch: 7 [57600/60000 (96%)]      Loss: 304.011200

Test set: Average loss: 153.6968, Accuracy: 7046/10000 (70%)

Train Epoch: 8 [0/60000 (0%)]   Loss: 178.044739
Train Epoch: 8 [6400/60000 (11%)]       Loss: 206.066025
Train Epoch: 8 [12800/60000 (21%)]      Loss: 116.606476
Train Epoch: 8 [19200/60000 (32%)]      Loss: 315.435089
Train Epoch: 8 [25600/60000 (43%)]      Loss: 174.898361
Train Epoch: 8 [32000/60000 (53%)]      Loss: 131.582291
Train Epoch: 8 [38400/60000 (64%)]      Loss: 317.067993
Train Epoch: 8 [44800/60000 (75%)]      Loss: 201.001022
Train Epoch: 8 [51200/60000 (85%)]      Loss: 172.404221
Train Epoch: 8 [57600/60000 (96%)]      Loss: 48.704540

Test set: Average loss: 260.7458, Accuracy: 6494/10000 (65%)

Train Epoch: 9 [0/60000 (0%)]   Loss: 264.489136
Train Epoch: 9 [6400/60000 (11%)]       Loss: 102.425941
Train Epoch: 9 [12800/60000 (21%)]      Loss: 353.628601
Train Epoch: 9 [19200/60000 (32%)]      Loss: 308.383850
Train Epoch: 9 [25600/60000 (43%)]      Loss: 336.653168
Train Epoch: 9 [32000/60000 (53%)]      Loss: 436.231415
Train Epoch: 9 [38400/60000 (64%)]      Loss: 139.269958
Train Epoch: 9 [44800/60000 (75%)]      Loss: 164.501450
Train Epoch: 9 [51200/60000 (85%)]      Loss: 98.646729
Train Epoch: 9 [57600/60000 (96%)]      Loss: 91.241409

Test set: Average loss: 293.0139, Accuracy: 6489/10000 (65%)

Train Epoch: 10 [0/60000 (0%)]  Loss: 437.896942
Train Epoch: 10 [6400/60000 (11%)]      Loss: 101.765732
Train Epoch: 10 [12800/60000 (21%)]     Loss: 371.181915
Train Epoch: 10 [19200/60000 (32%)]     Loss: 88.069504
Train Epoch: 10 [25600/60000 (43%)]     Loss: 282.099945
Train Epoch: 10 [32000/60000 (53%)]     Loss: 73.224792
Train Epoch: 10 [38400/60000 (64%)]     Loss: 356.815826
Train Epoch: 10 [44800/60000 (75%)]     Loss: 133.444214
Train Epoch: 10 [51200/60000 (85%)]     Loss: 145.617142
Train Epoch: 10 [57600/60000 (96%)]     Loss: 107.395584

Test set: Average loss: 286.4534, Accuracy: 6393/10000 (64%)
```

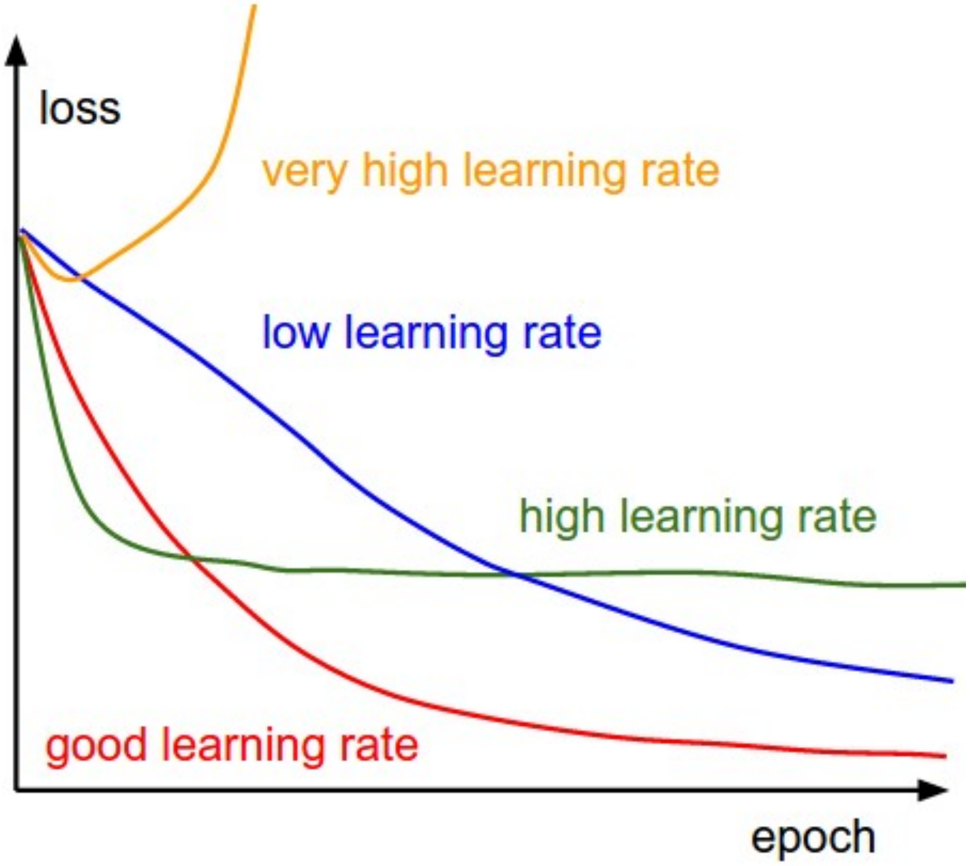
In [20]:
```
plt.plot(loss_g)
plt.xlabel("Iterations x Epoch")
plt.ylabel("Loss")
plt.title("Loss as a function of time")
```

Out[20]: <matplotlib.text.Text at 0x7faa1460d9b0>



Overshoot

Choosing too large a value for the learning rate, makes the training process (optimisation) unstable. This is because higher learning rates will decay the loss faster, but they get stuck at worse values of loss (green line in image below) and in our case, we see that the loss flucutates and lot and gets stuck around loss values > 100, while with a lower lr we were able to see loss value as low as ~0.5. This is because there is too much "energy" in the optimization and the parameters are bouncing around chaotically, unable to settle in a nice spot in the optimization landscape.



Training a Convolutional Network on CIFAR [50%]

To change over to the CIFAR-10 dataset, change the `options` cell's `dataset` variable to `'cifar10'`.

Hints: [Follow the first PyTorch tutorial (http://pytorch.org/tutorials/beginner/blitz/neural_networks_tutorial.html#sphx-glr-beginner-blitz-neural-networks-tutorial-py)](http://pytorch.org/tutorials/beginner/blitz/neural_networks_tutorial.html#sphx-glr-beginner-blitz-neural-networks-tutorial-py) or look at the [MNIST example (https://github.com/pytorch/examples/tree/master/mnist)](https://github.com/pytorch/examples/tree/master/mnist)

In [21]:
```
dataset = 'cifar10'
data_transform = transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
])
trainset = datasets.CIFAR10(root='.', train=True, download=True, tr
ansform=data_transform)
testset = datasets.CIFAR10(root='.', train=True, download=True, tra
nsform=data_transform)

train_loader = torch.utils.data.DataLoader(trainset, batch_size=bat
ch_size, shuffle=True, num_workers=0)
test_loader  = torch.utils.data.DataLoader(testset, batch_size=batc
h_size, shuffle=False, num_workers=0)
```

```
Files already downloaded and verified
Files already downloaded and verified
```

- Create a convolutional network with the following architecture:
  - Convolution with 5 by 5 filters, 16 feature maps + Tanh nonlinearity.
  - 2 by 2 max pooling.
  - Convolution with 5 by 5 filters, 128 feature maps + Tanh nonlinearity.
  - 2 by 2 max pooling.
  - Flatten to vector.
  - Linear layer with 64 hidden units + Tanh nonlinearity.
  - Linear layer to 10 output units.

In [22]:
```
## network and optimizer
if dataset == 'mnist':
    num_inputs = 784
elif dataset == 'cifar10':
    num_inputs = 3072


class Net(nn.Module):
    def __init__(self, num_channels, num_outputs):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(num_channels, 16, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(16, 128, 5)
        self.fc1 = nn.Linear(128 * 5 * 5, 64)
        self.fc2 = nn.Linear(64, num_outputs)

    def forward(self, x):
        x = self.pool(F.tanh(self.conv1(x)))
        x = self.pool(F.tanh(self.conv2(x)))
#         print(x.size())
        x = x.view(-1, 128 * 5 * 5)
        x = F.tanh(self.fc1(x))
        x = self.fc2(x)
        return x

num_channels = iter(train_loader).next()[0].size()[1]
network = Net(num_channels, num_outputs=10)
network.cuda()
optimizer = optim.SGD(network.parameters(), lr=lr)
```

Train it for 20 epochs on the CIFAR-10 training set and copy the output into your report, along with a image of the first layer filters.

In [23]:
```
epochs = 20

loss_g = []
for epoch in range(1, 1 + epochs):
    loss_g.extend(train(epoch))
    test()
```

```
Train Epoch: 1 [0/50000 (0%)]	Loss: 2.311074
Train Epoch: 1 [6400/50000 (13%)]	Loss: 2.168980
Train Epoch: 1 [12800/50000 (26%)]	Loss: 2.061869
```

```
Train Epoch: 1 [19200/50000 (38%)]	Loss: 1.884514
Train Epoch: 1 [25600/50000 (51%)]	Loss: 1.868822
Train Epoch: 1 [32000/50000 (64%)]	Loss: 1.917039
Train Epoch: 1 [38400/50000 (77%)]	Loss: 1.910085
Train Epoch: 1 [44800/50000 (90%)]	Loss: 1.787620

Test set: Average loss: 1.7848, Accuracy: 18857/50000 (38%)

Train Epoch: 2 [0/50000 (0%)]	Loss: 1.625484
Train Epoch: 2 [6400/50000 (13%)]	Loss: 1.762575
Train Epoch: 2 [12800/50000 (26%)]	Loss: 1.773592
Train Epoch: 2 [19200/50000 (38%)]	Loss: 1.785707
Train Epoch: 2 [25600/50000 (51%)]	Loss: 1.722296
Train Epoch: 2 [32000/50000 (64%)]	Loss: 1.567242
Train Epoch: 2 [38400/50000 (77%)]	Loss: 1.516354
Train Epoch: 2 [44800/50000 (90%)]	Loss: 1.783387

Test set: Average loss: 1.6084, Accuracy: 21455/50000 (43%)

Train Epoch: 3 [0/50000 (0%)]	Loss: 1.623398
Train Epoch: 3 [6400/50000 (13%)]	Loss: 1.670742
Train Epoch: 3 [12800/50000 (26%)]	Loss: 1.553486
Train Epoch: 3 [19200/50000 (38%)]	Loss: 1.618239
Train Epoch: 3 [25600/50000 (51%)]	Loss: 1.653537
Train Epoch: 3 [32000/50000 (64%)]	Loss: 1.549494
Train Epoch: 3 [38400/50000 (77%)]	Loss: 1.590208
Train Epoch: 3 [44800/50000 (90%)]	Loss: 1.426031

Test set: Average loss: 1.5041, Accuracy: 23038/50000 (46%)

Train Epoch: 4 [0/50000 (0%)]	Loss: 1.452612
Train Epoch: 4 [6400/50000 (13%)]	Loss: 1.289611
Train Epoch: 4 [12800/50000 (26%)]	Loss: 1.479025
Train Epoch: 4 [19200/50000 (38%)]	Loss: 1.432477
Train Epoch: 4 [25600/50000 (51%)]	Loss: 1.581997
Train Epoch: 4 [32000/50000 (64%)]	Loss: 1.446263
Train Epoch: 4 [38400/50000 (77%)]	Loss: 1.541313
Train Epoch: 4 [44800/50000 (90%)]	Loss: 1.440764

Test set: Average loss: 1.3776, Accuracy: 25472/50000 (51%)

Train Epoch: 5 [0/50000 (0%)]	Loss: 1.505205
Train Epoch: 5 [6400/50000 (13%)]	Loss: 1.312487
Train Epoch: 5 [12800/50000 (26%)]	Loss: 1.334268
Train Epoch: 5 [19200/50000 (38%)]	Loss: 1.375814
Train Epoch: 5 [25600/50000 (51%)]	Loss: 1.353024
Train Epoch: 5 [32000/50000 (64%)]	Loss: 1.160980
Train Epoch: 5 [38400/50000 (77%)]	Loss: 1.364076
Train Epoch: 5 [44800/50000 (90%)]	Loss: 1.423528

Test set: Average loss: 1.3137, Accuracy: 26589/50000 (53%)

Train Epoch: 6 [0/50000 (0%)]	Loss: 1.311993
Train Epoch: 6 [6400/50000 (13%)]	Loss: 1.216267
Train Epoch: 6 [12800/50000 (26%)]	Loss: 1.233445
Train Epoch: 6 [19200/50000 (38%)]	Loss: 1.325149
Train Epoch: 6 [25600/50000 (51%)]	Loss: 1.156881
```

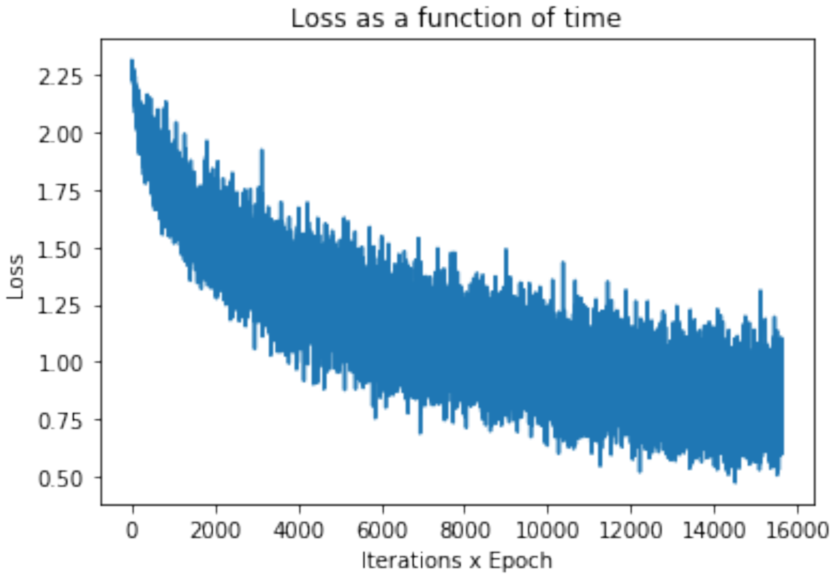
```
Train Epoch: 6 [32000/50000 (64%)]      Loss: 1.255083
Train Epoch: 6 [38400/50000 (77%)]      Loss: 1.133017
Train Epoch: 6 [44800/50000 (90%)]      Loss: 1.294857

Test set: Average loss: 1.3271, Accuracy: 26516/50000 (53%)

Train Epoch: 7 [0/50000 (0%)]   Loss: 1.590864
Train Epoch: 7 [6400/50000 (13%)]       Loss: 1.328382
Train Epoch: 7 [12800/50000 (26%)]      Loss: 1.319315
Train Epoch: 7 [19200/50000 (38%)]      Loss: 1.103988
Train Epoch: 7 [25600/50000 (51%)]      Loss: 1.399049
Train Epoch: 7 [32000/50000 (64%)]      Loss: 1.003780
Train Epoch: 7 [38400/50000 (77%)]      Loss: 1.199377
Train Epoch: 7 [44800/50000 (90%)]      Loss: 0.926778

Test set: Average loss: 1.2909, Accuracy: 27337/50000 (55%)

Train Epoch: 8 [0/50000 (0%)]   Loss: 1.163183
Train Epoch: 8 [6400/50000 (13%)]       Loss: 1.080150
Train Epoch: 8 [12800/50000 (26%)]      Loss: 1.157052
Train Epoch: 8 [19200/50000 (38%)]      Loss: 1.273702
Train Epoch: 8 [25600/50000 (51%)]      Loss: 1.034777
Train Epoch: 8 [32000/50000 (64%)]      Loss: 1.269905
Train Epoch: 8 [38400/50000 (77%)]      Loss: 0.978868
Train Epoch: 8 [44800/50000 (90%)]      Loss: 1.514963

Test set: Average loss: 1.1285, Accuracy: 30180/50000 (60%)

Train Epoch: 9 [0/50000 (0%)]   Loss: 1.199980
Train Epoch: 9 [6400/50000 (13%)]       Loss: 1.203605
Train Epoch: 9 [12800/50000 (26%)]      Loss: 1.270540
Train Epoch: 9 [19200/50000 (38%)]      Loss: 1.482030
Train Epoch: 9 [25600/50000 (51%)]      Loss: 0.982017
Train Epoch: 9 [32000/50000 (64%)]      Loss: 1.121023
Train Epoch: 9 [38400/50000 (77%)]      Loss: 1.221995
Train Epoch: 9 [44800/50000 (90%)]      Loss: 0.847705

Test set: Average loss: 1.1395, Accuracy: 29868/50000 (60%)

Train Epoch: 10 [0/50000 (0%)]  Loss: 0.970143
Train Epoch: 10 [6400/50000 (13%)]      Loss: 0.887521
Train Epoch: 10 [12800/50000 (26%)]     Loss: 1.001829
Train Epoch: 10 [19200/50000 (38%)]     Loss: 1.025421
Train Epoch: 10 [25600/50000 (51%)]     Loss: 1.276407
Train Epoch: 10 [32000/50000 (64%)]     Loss: 1.312467
Train Epoch: 10 [38400/50000 (77%)]     Loss: 1.101873
Train Epoch: 10 [44800/50000 (90%)]     Loss: 1.071171

Test set: Average loss: 1.0706, Accuracy: 31250/50000 (62%)

Train Epoch: 11 [0/50000 (0%)]  Loss: 1.092624
Train Epoch: 11 [6400/50000 (13%)]      Loss: 1.062100
Train Epoch: 11 [12800/50000 (26%)]     Loss: 0.963148
Train Epoch: 11 [19200/50000 (38%)]     Loss: 0.947381
Train Epoch: 11 [25600/50000 (51%)]     Loss: 0.829268
Train Epoch: 11 [32000/50000 (64%)]     Loss: 0.988034
Train Epoch: 11 [38400/50000 (77%)]     Loss: 1.022674
```

```
Train Epoch: 11 [44800/50000 (90%)]	Loss: 1.207424

Test set: Average loss: 1.0385, Accuracy: 31701/50000 (63%)

Train Epoch: 12 [0/50000 (0%)]	Loss: 1.010774
Train Epoch: 12 [6400/50000 (13%)]	Loss: 0.885834
Train Epoch: 12 [12800/50000 (26%)]	Loss: 0.990990
Train Epoch: 12 [19200/50000 (38%)]	Loss: 1.084442
Train Epoch: 12 [25600/50000 (51%)]	Loss: 1.088133
Train Epoch: 12 [32000/50000 (64%)]	Loss: 0.900626
Train Epoch: 12 [38400/50000 (77%)]	Loss: 1.286531
Train Epoch: 12 [44800/50000 (90%)]	Loss: 1.029789

Test set: Average loss: 0.9913, Accuracy: 32471/50000 (65%)

Train Epoch: 13 [0/50000 (0%)]	Loss: 0.981126
Train Epoch: 13 [6400/50000 (13%)]	Loss: 0.793888
Train Epoch: 13 [12800/50000 (26%)]	Loss: 0.954074
Train Epoch: 13 [19200/50000 (38%)]	Loss: 1.034053
Train Epoch: 13 [25600/50000 (51%)]	Loss: 0.897521
Train Epoch: 13 [32000/50000 (64%)]	Loss: 0.942610
Train Epoch: 13 [38400/50000 (77%)]	Loss: 0.856479
Train Epoch: 13 [44800/50000 (90%)]	Loss: 1.030479

Test set: Average loss: 0.9710, Accuracy: 33100/50000 (66%)

Train Epoch: 14 [0/50000 (0%)]	Loss: 1.093205
Train Epoch: 14 [6400/50000 (13%)]	Loss: 1.013026
Train Epoch: 14 [12800/50000 (26%)]	Loss: 0.916090
Train Epoch: 14 [19200/50000 (38%)]	Loss: 0.810805
Train Epoch: 14 [25600/50000 (51%)]	Loss: 1.047452
Train Epoch: 14 [32000/50000 (64%)]	Loss: 0.842551
Train Epoch: 14 [38400/50000 (77%)]	Loss: 1.131165
Train Epoch: 14 [44800/50000 (90%)]	Loss: 0.981667

Test set: Average loss: 0.9882, Accuracy: 32428/50000 (65%)

Train Epoch: 15 [0/50000 (0%)]	Loss: 1.098027
Train Epoch: 15 [6400/50000 (13%)]	Loss: 0.832118
Train Epoch: 15 [12800/50000 (26%)]	Loss: 0.910048
Train Epoch: 15 [19200/50000 (38%)]	Loss: 1.074954
Train Epoch: 15 [25600/50000 (51%)]	Loss: 0.928003
Train Epoch: 15 [32000/50000 (64%)]	Loss: 0.895588
Train Epoch: 15 [38400/50000 (77%)]	Loss: 1.029839
Train Epoch: 15 [44800/50000 (90%)]	Loss: 0.765426

Test set: Average loss: 0.9563, Accuracy: 32882/50000 (66%)

Train Epoch: 16 [0/50000 (0%)]	Loss: 0.932784
Train Epoch: 16 [6400/50000 (13%)]	Loss: 1.105722
Train Epoch: 16 [12800/50000 (26%)]	Loss: 0.938665
Train Epoch: 16 [19200/50000 (38%)]	Loss: 0.682375
Train Epoch: 16 [25600/50000 (51%)]	Loss: 1.020907
Train Epoch: 16 [32000/50000 (64%)]	Loss: 0.671075
Train Epoch: 16 [38400/50000 (77%)]	Loss: 0.843965
Train Epoch: 16 [44800/50000 (90%)]	Loss: 0.783031
```

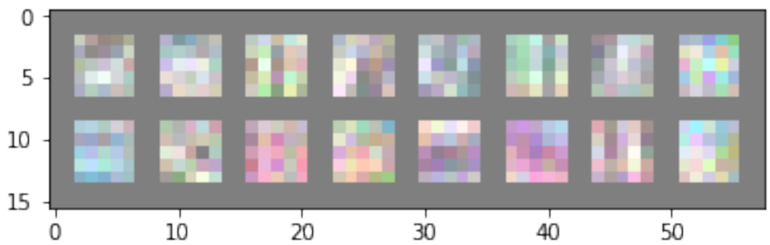
```
Test set: Average loss: 0.9449, Accuracy: 33389/50000 (67%)

Train Epoch: 17 [0/50000 (0%)]	Loss: 0.898421
Train Epoch: 17 [6400/50000 (13%)]	Loss: 0.973435
Train Epoch: 17 [12800/50000 (26%)]	Loss: 0.864367
Train Epoch: 17 [19200/50000 (38%)]	Loss: 0.893914
Train Epoch: 17 [25600/50000 (51%)]	Loss: 0.936469
Train Epoch: 17 [32000/50000 (64%)]	Loss: 0.895847
Train Epoch: 17 [38400/50000 (77%)]	Loss: 0.975957
Train Epoch: 17 [44800/50000 (90%)]	Loss: 0.837127

Test set: Average loss: 1.0627, Accuracy: 31139/50000 (62%)

Train Epoch: 18 [0/50000 (0%)]	Loss: 1.079416
Train Epoch: 18 [6400/50000 (13%)]	Loss: 1.010369
Train Epoch: 18 [12800/50000 (26%)]	Loss: 0.649134
Train Epoch: 18 [19200/50000 (38%)]	Loss: 0.831679
Train Epoch: 18 [25600/50000 (51%)]	Loss: 0.916567
Train Epoch: 18 [32000/50000 (64%)]	Loss: 1.006504
Train Epoch: 18 [38400/50000 (77%)]	Loss: 0.947578
Train Epoch: 18 [44800/50000 (90%)]	Loss: 0.944992

Test set: Average loss: 0.8388, Accuracy: 35285/50000 (71%)

Train Epoch: 19 [0/50000 (0%)]	Loss: 0.757807
Train Epoch: 19 [6400/50000 (13%)]	Loss: 1.008512
Train Epoch: 19 [12800/50000 (26%)]	Loss: 0.783986
Train Epoch: 19 [19200/50000 (38%)]	Loss: 0.695759
Train Epoch: 19 [25600/50000 (51%)]	Loss: 0.787887
Train Epoch: 19 [32000/50000 (64%)]	Loss: 0.749146
Train Epoch: 19 [38400/50000 (77%)]	Loss: 0.921931
Train Epoch: 19 [44800/50000 (90%)]	Loss: 0.806059

Test set: Average loss: 0.8064, Accuracy: 36024/50000 (72%)

Train Epoch: 20 [0/50000 (0%)]	Loss: 0.807722
Train Epoch: 20 [6400/50000 (13%)]	Loss: 0.763600
Train Epoch: 20 [12800/50000 (26%)]	Loss: 0.789367
Train Epoch: 20 [19200/50000 (38%)]	Loss: 0.804348
Train Epoch: 20 [25600/50000 (51%)]	Loss: 0.764329
Train Epoch: 20 [32000/50000 (64%)]	Loss: 0.768273
Train Epoch: 20 [38400/50000 (77%)]	Loss: 0.610842
Train Epoch: 20 [44800/50000 (90%)]	Loss: 0.660720

Test set: Average loss: 0.7875, Accuracy: 36237/50000 (72%)
```

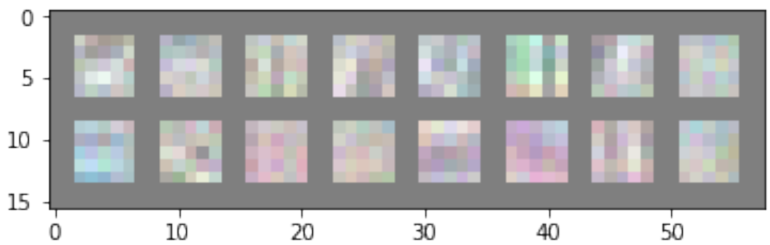
In [24]:
```
plt.plot(loss_g)
plt.xlabel("Iterations x Epoch")
plt.ylabel("Loss")
plt.title("Loss as a function of time")
```

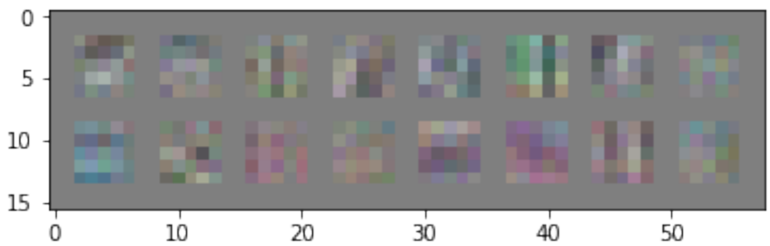
Out[24]: <matplotlib.text.Text at 0x7faa1454b748>



In [25]:
```
for x in network.modules():
    if isinstance(x, nn.Conv2d):
        imshow(utils.make_grid(x.weight.data.cpu(),normalize=True,
scale_each=True))
        imshow(utils.make_grid(x.weight.data.cpu(),normalize=True))
        imshow(utils.make_grid(x.weight.data.cpu()))
        break
```



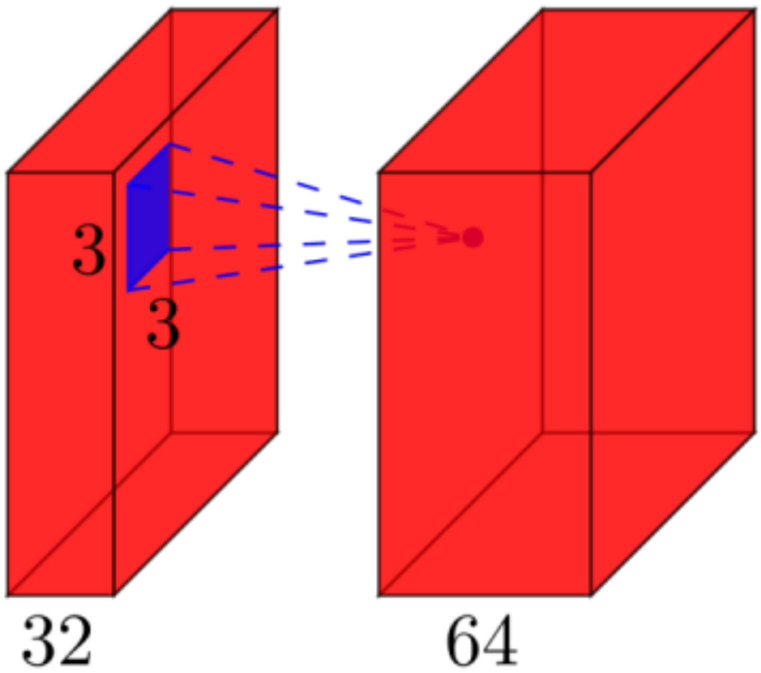




- Give a breakdown of the parameters within the above model, and the overall number.

Number of learnable parameters per different type of layer is as follows:

- **Input layer:** All the input layer does is read the input image, so there are no learnable parameters here.
- **Convolutional layers:** Consider a convolutional layer which takes `l` feature maps at the input, and has `k` feature maps as output. The filter size is `n x m`. For example, this will look like this:



Here, the input has `l=32` feature maps as input, `k=64` feature maps as output, and the filter size is `n=3 x m=3`. It is important to understand, that we don't simply have a `3x3` filter, but actually a `3x3x32` filter, as our input has 32 dimensions. And we learn 64 different `3x3x32` filters. Thus, the total number of weights is `n*m*k*l`. Then, there is also a bias term for each feature map, so we have a total number of parameters of `(n*m*l+1)*k`.

- Pooling layers: The pooling layers e.g. do the following: "replace a 2x2 neighborhood by its maximum value". So there is no parameter you could learn in a pooling layer.
- Fully-connected layers: In a fully-connected layer, all input units have a separate weight to each output unit. For `n` inputs and `m` outputs, the number of weights is `n*m`. Additionally, you have a bias for each output node, so you are at `(n+1)*m` parameters.
- Output layer: The output layer is a normal fully-connected layer, so `(n+1)*m` parameters, where `n` is the number of inputs and `m` is the number of outputs.

Reference: [https://stackoverflow.com/questions/42786717/how-to-calculate-learnable-parameters-for-neural-network (https://stackoverflow.com/questions/42786717/how-to-calculate-learnable-parameters-for-neural-network)](https://stackoverflow.com/questions/42786717/how-to-calculate-learnable-parameters-for-neural-network)

All the different parts of the model can be seen below:

In [27]:
```
network
```

Out[27]:
```
Net (
  (conv1): Conv2d(3, 16, kernel_size=(5, 5), stride=(1, 1))
  (pool): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
  (conv2): Conv2d(16, 128, kernel_size=(5, 5), stride=(1, 1))
  (fc1): Linear (3200 -> 64)
  (fc2): Linear (64 -> 10)
)
```

The total number of learnable parameters are calculated as follows where the bias for each layer are after the respective layer.

In [26]:
```
params = list(network.parameters())
print(len(params))
total_parameter_count = 0
for param in params:
    param_count = np.prod(param.size())
    total_parameter_count += param_count
    print(param.size())
print("Total number of parameters:", total_parameter_count)
```

```
8
torch.Size([16, 3, 5, 5])
torch.Size([16])
torch.Size([128, 16, 5, 5])
torch.Size([128])
torch.Size([64, 3200])
torch.Size([64])
torch.Size([10, 64])
torch.Size([10])
Total number of parameters: 258058
```