Predicting a sine wave

Scripot to predict a sine wave and get practice using LSTM layers in a recurrent neural network.

Sources:

Soumith's Githib - Time Sequence Prediction

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# Generating Sine Wave Data
```

Generating Sine Wave Data

```
import numpy as np
import torch
import matplotlib.pyplot as plt
import cycler
```

Define Parameters for various sine waves

[0 0 0 0 0] [0 0 0 0 0]]

```
[42] np.random.seed(2)

T = 20
L = 1000
N = 100

[43] #Create an empty np matrix (of zeros) with shape 100x1000
x = np.zeros((N, L), 'int64')
print("Shape of matrix x:", x.shape)
print(" ")
print("Top left 5x5 matrix of matrix (x):")
print(x[:5, :5])

Shape of matrix x: (100, 1000)

Top left 5x5 matrix of matrix (x):
[[0 0 0 0 0]
[0 0 0 0 0]
[0 0 0 0 0]
```

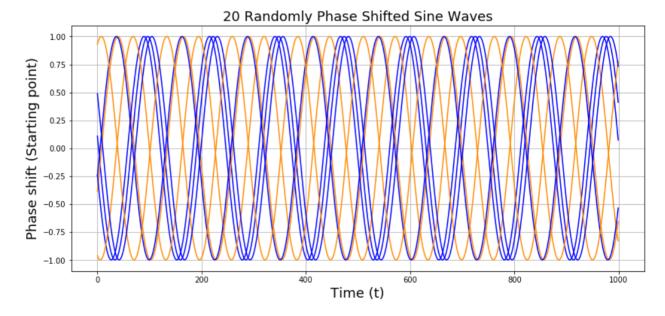
```
[44] linear_vector = np.array(range(L))
x[:] = linear_vector + np.random.randint(-4 * T, 4 * T, N).reshape(N, 1)
```

These will be the starting points of our 100 phase shifted sine waves

```
data = np.sin(x / 1.0 / T).astype('float64')

fig = plt.figure(figsize=(30, 6))
    ax1 = fig.add_subplot(121)
    plt.gca().set_prop_cycle('color', ['blue', 'darkorange'])

plt.plot(data[0, :])
    plt.plot(data[1, :])
    plt.plot(data[2, :])
    plt.plot(data[3, :])
    plt.plot(data[4, :])
    plt.plot(data[5, :])
    plt.plot(data[6, :])
    plt.xlabel('Time (t)', fontsize = 18)
    plt.ylabel('Phase shift (Starting point)', fontsize = 18)
    plt.title('20 Randomly Phase Shifted Sine Waves', fontsize = 18)
    plt.grid()
```



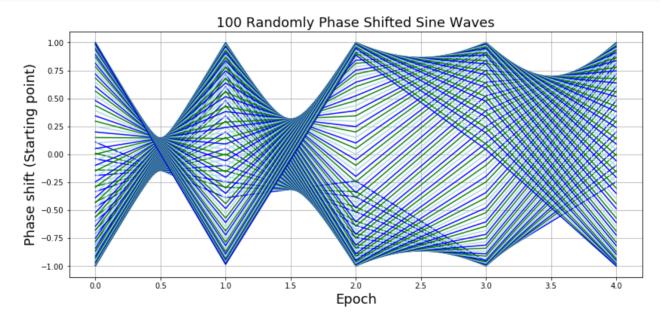
```
fig = plt.figure(figsize=(30, 6))
ax1 = fig.add_subplot(121)
plt.gca().set_prop_cycle('color', ['blue', 'lightblue', 'green'])

plt.plot(data[:6, :20])
plt.xlabel('Epoch', fontsize = 18)
plt.ylabel('Phase shift (Starting point)', fontsize = 18)
plt.title('100 Randomly Phase Shifted Sine Waves', fontsize = 18)
plt.grid()
```



```
fig = plt.figure(figsize=(30, 6))
ax1 = fig.add_subplot(121)
plt.gca().set_prop_cycle('color', ['blue', 'lightblue', 'green'])

plt.plot(data[:5, :100])
plt.xlabel('Epoch', fontsize = 18)
plt.ylabel('Phase shift (Starting point)', fontsize = 18)
plt.title('100 Randomly Phase Shifted Sine Waves', fontsize = 18)
plt.grid()
```



Define Network Parameters

Now that we have several randomly phase shifted sine waves stored in 'data' we can begin to build out the network we will use for prediction

```
from __future__ import print_function
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import matplotlib
matplotlib.use('Agg')
import matplotlib.pyplot as plt
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:7:
UserWarning:
This call to matplotlib.use() has no effect because the backend has already
been chosen; matplotlib.use() must be called *before* pylab,
matplotlib.pyplot,
or matplotlib.backends is imported for the first time.
The backend was *originally* set to
'module://ipykernel.pylab.backend_inline' by the following code:
  File "/anaconda3/lib/python3.6/runpy.py", line 193, in
_run_module_as_main
    "__main__", mod_spec)
  File "/anaconda3/lib/python3.6/runpy.py", line 85, in _run_code
    exec(code, run_globals)
  File "/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py", line
16, in <module>
    app.launch_new_instance()
  File "/anaconda3/lib/python3.6/site-
packages/traitlets/config/application.py", line 658, in launch_instance
    app.start()
  File "/anaconda3/lib/python3.6/site-packages/ipykernel/kernelapp.py",
line 486, in start
    self.io_loop.start()
  File "/anaconda3/lib/python3.6/site-
packages/tornado/platform/asyncio.py", line 127, in start
    self.asyncio_loop.run_forever()
  File "/anaconda3/lib/python3.6/asyncio/base_events.py", line 422, in
run_forever
    self._run_once()
  File "/anaconda3/lib/python3.6/asyncio/base_events.py", line 1432, in
_run_once
    handle._run()
  File "/anaconda3/lib/pvthon3.6/asvncio/events.pv". line 145. in run
class Sequence(nn.Module):
    def __init__(self):
        super(Sequence, self).__init__()
        self.lstm1 = nn.LSTMCell(1, 51)
        self.lstm2 = nn.LSTMCell(51, 51)
        self.linear = nn.Linear(51, 1)
    def forward(self, input, future = 0):
        outputs = []
        h_t = torch.zeros(input.size(0), 51, dtype=torch.double)
        c_t = torch.zeros(input.size(0), 51, dtype=torch.double)
```

```
h_t2 = torch.zeros(input.size(0), 51, dtype=torch.double)
              c_t2 = torch.zeros(input.size(0), 51, dtype=torch.double)
              for i, input_t in enumerate(input.chunk(input.size(1), dim=1)):
                  h_t, c_t = self.lstm1(input_t, (h_t, c_t))
                  h_t2, c_t2 = self.lstm2(h_t, (h_t2, c_t2))
                  output = self.linear(h_t2)
                  outputs += [output]
              for i in range(future):# if we should predict the future
                  h_t, c_t = self.lstm1(output, (h_t, c_t))
                  h_t2, c_t2 = self.lstm2(h_t, (h_t2, c_t2))
                  output = self.linear(h_t2)
                  outputs += [output]
              outputs = torch.stack(outputs, 1).squeeze(2)
              return outputs
     # set random seed to 0
      np.random.seed(0)
      torch.manual_seed(0)
      #Define data for training and testing
      input = torch.from_numpy(data[3:, :-1])
      target = torch.from_numpy(data[3:, 1:])
      test_input = torch.from_numpy(data[:3, :-1])
      test_target = torch.from_numpy(data[:3, 1:])
     # build the model
      seq = Sequence()
      seq.double()
      criterion = nn.MSELoss()
      # use LBFGS as optimizer since we can load the whole data to train
      optimizer = optim.LBFGS(seq.parameters(), lr=0.8)
[53]
     #begin to train
      for i in range(15):
          print('STEP: ', i)
          def closure():
              optimizer.zero_grad()
              out = seq(input)
              loss = criterion(out, target)
              print('loss:', loss.item())
              loss.backward()
              return loss
          optimizer.step(closure)
          # begin to predict, no need to track gradient here
```

```
with torch.no_grad():
         future = 1000
         pred = seq(test_input, future=future)
         loss = criterion(pred[:, :-future], test_target)
         print('test loss:', loss.item())
         y = pred.detach().numpy()
    # draw the result
    plt.figure(figsize=(30,10))
    plt.title('Predict future values for time sequences\n(Dashlines are p
    plt.xlabel('x', fontsize=20)
    plt.ylabel('y', fontsize=20)
    plt.xticks(fontsize=20)
    plt.yticks(fontsize=20)
    def draw(yi, color):
         plt.plot(np.arange(input.size(1)), yi[:input.size(1)], color, lin-
         plt.plot(np.arange(input.size(1), input.size(1) + future), yi[input.size(1) + future)
    draw(y[0], 'r')
    draw(y[1], 'g')
    draw(y[2], 'b')
-0.75
-1.00
                250
                         500
                                                             1500
                             Predict future values for time sequences
                                (Dashlines are predicted values)
 1.0
 0.5
> 0.0
-0.5
 -1.0
               250
                        500
                                 750
                                          1000
                                                   1250
                                                            1500
                                                                      1750
                                                                               2000
                             Predict future values for time sequences
                                (Dashlines are predicted values)
 1.00
 0.75
 0.50
 0.25
 -0.25
-0.50
-0.75
 -1.00
                                           1000
                                                    1250
                                                             1500
                                                                      1750
                                                                               2000
                             Predict future values for time sequences
                                (Dashlines are predicted values)
```

We can see that the final iteration produced a result with a test loss of $6*10^{-6}$ and a qualitatively accurate visual continuation of our sine wave.