sequence

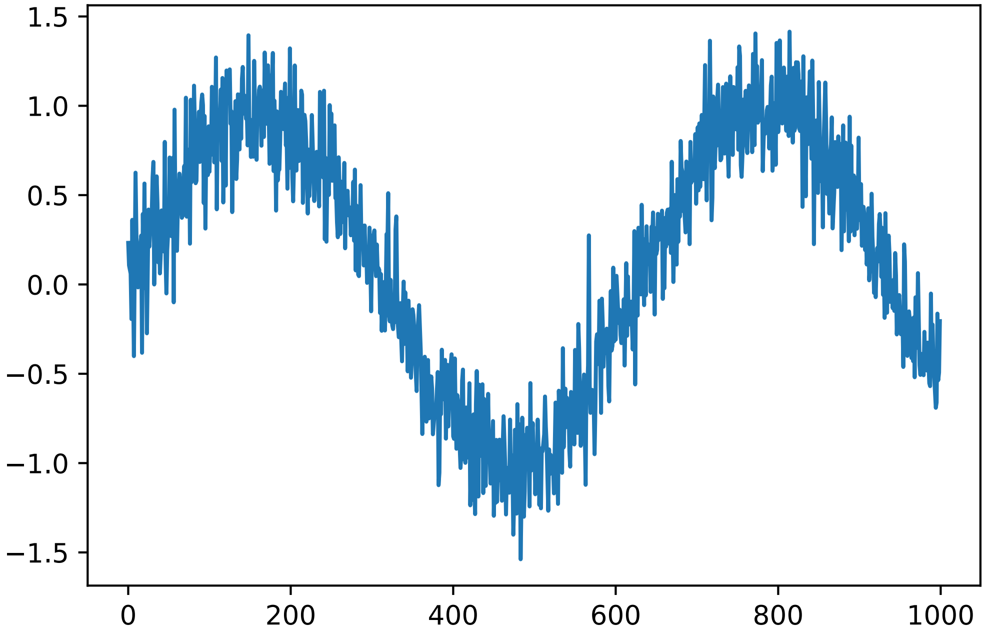
April 9, 2019

0.0.1 Autoregressive Models

```
In [1]: from mxnet import autograd, nd, gluon, init
        import d2l
        # display routines
        %matplotlib inline
        from matplotlib import pyplot as plt
        from IPython import display
        display.set_matplotlib_formats('svg')

        embedding = 4 # embedding dimension for autoregressive model
        T = 1000      # generate a total of 1000 points
        time = nd.arange(0,T)
        x = nd.sin(0.01 * time) + 0.2 * nd.random.normal(shape=(T))
```

```
In [2]: plt.plot(time.asnumpy(), x.asnumpy());
```



0.0.2 Generating the Regression Dataset

```
In [3]: features = nd.zeros((T-embedding, embedding))
        for i in range(embedding):
            features[:,i] = x[i:T-embedding+i]
        labels = x[embedding:]

        ntrain = 600
        train_data = gluon.data.ArrayDataset(features[:ntrain,:], labels[:ntrain])
        test_data  = gluon.data.ArrayDataset(features[ntrain:,:], labels[ntrain:])

        def get_net():
            net = gluon.nn.Sequential()
            net.add(gluon.nn.Dense(10, activation='relu'))
            net.add(gluon.nn.Dense(10, activation='relu'))
            net.add(gluon.nn.Dense(1))
            net.initialize(init.Xavier())
            return net

        loss = gluon.loss.L2Loss()
```

0.0.3 Training

```
In [4]: # simple optimizer using adam, random shuffle and minibatch size 16
        def train_net(net, data, loss, epochs, learningrate):
            batch_size = 16
            trainer = gluon.Trainer(net.collect_params(), 'adam', {'learning_rate': learningra
            data_iter = gluon.data.DataLoader(data, batch_size, shuffle=True)
            for epoch in range(1, epochs + 1):
                for X, y in data_iter:
                    with autograd.record():
                        l = loss(net(X), y)
                    l.backward()
                    trainer.step(batch_size)
                l = loss(net(data[:][0]), nd.array(data[:][1]))
                print('epoch %d, loss: %f' % (epoch, l.mean().asnumpy()))
            return net
```

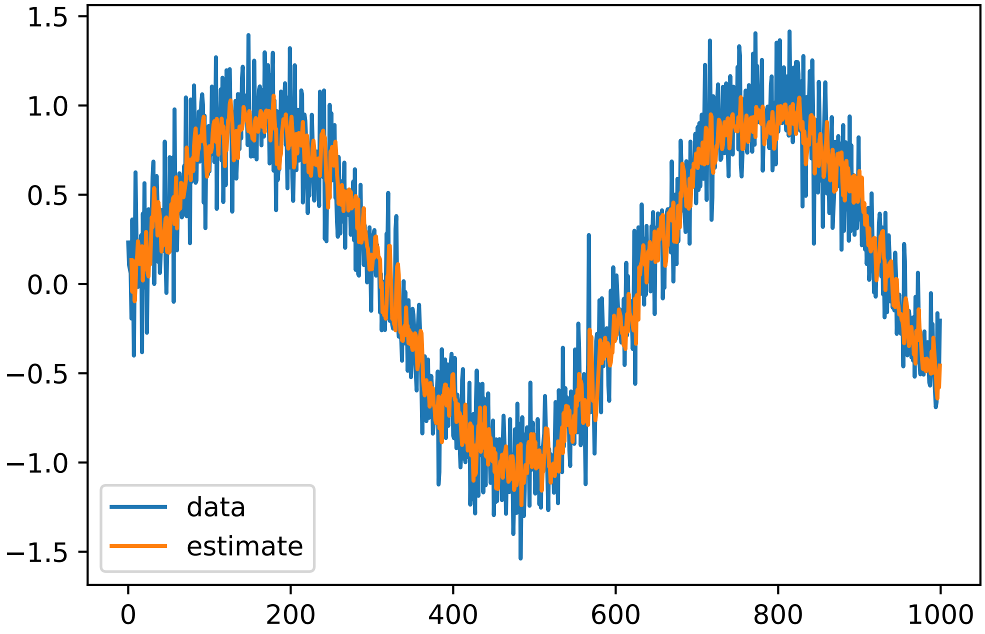
```
In [5]: net = get_net()
        net = train_net(net, train_data, loss, 10, 0.01)

        l = loss(net(test_data[:][0]), nd.array(test_data[:][1]))
        print('test loss: %f' % l.mean().asnumpy())
```

```
epoch 1, loss: 0.036634
epoch 2, loss: 0.030942
epoch 3, loss: 0.028760
epoch 4, loss: 0.028204
epoch 5, loss: 0.027514
epoch 6, loss: 0.027594
epoch 7, loss: 0.028184
epoch 8, loss: 0.028527
epoch 9, loss: 0.029737
epoch 10, loss: 0.026995
test loss: 0.024697
```

0.0.4 Results

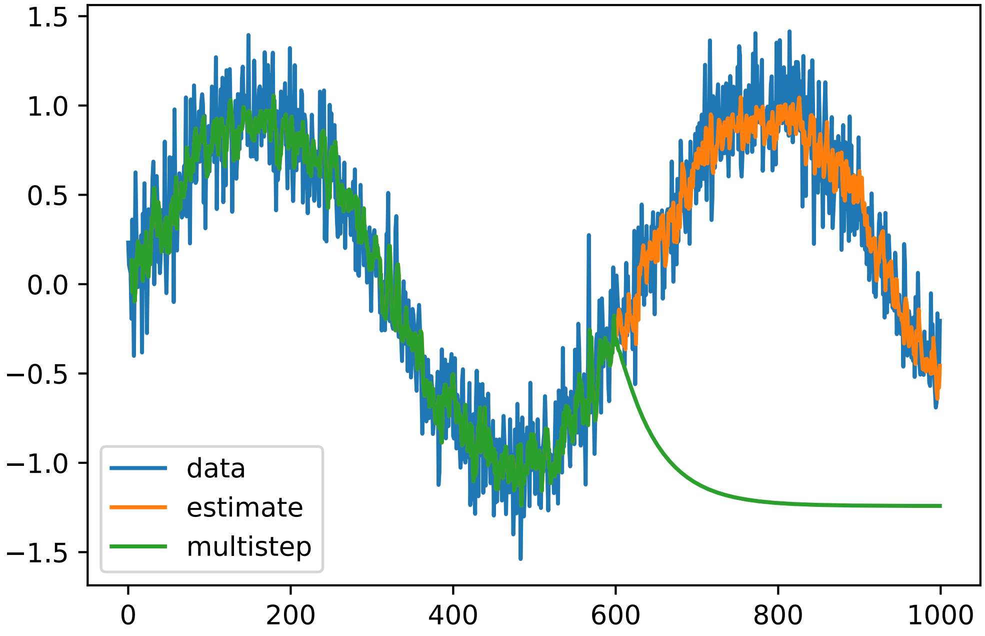
```
In [6]: estimates = net(features)
        plt.plot(time.asnumpy(), x.asnumpy(), label='data');
        plt.plot(time[embedding:].asnumpy(), estimates.asnumpy(), label='estimate');
        plt.legend();
```



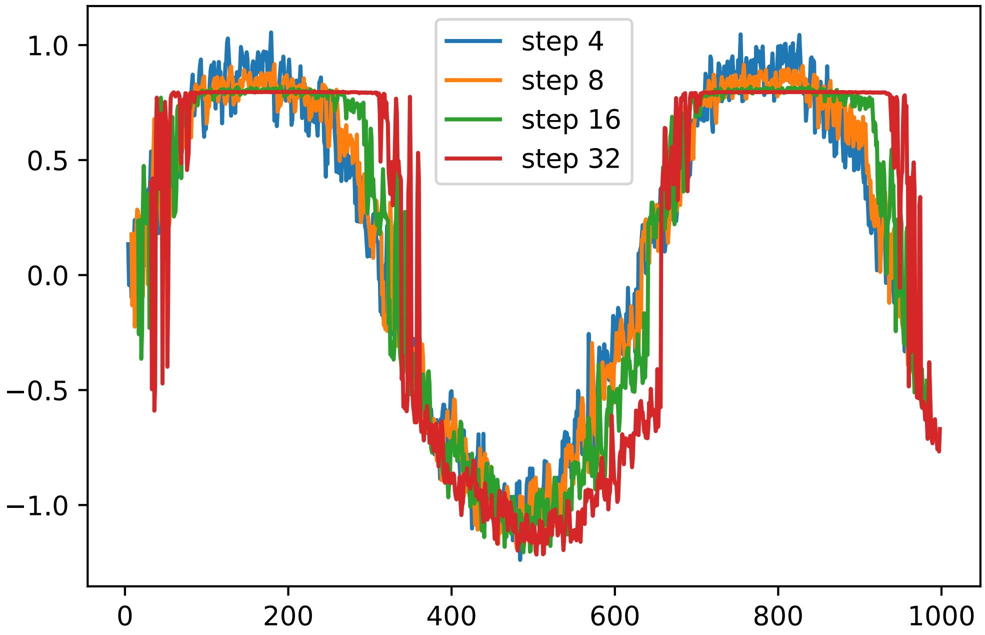
0.1 Predictions for more than 1 step

```
In [7]: predictions = nd.zeros_like(estimates)
        predictions[:(ntrain-embedding)] = estimates[:(ntrain-embedding)]
        for i in range(ntrain-embedding, T-embedding):
            predictions[i] = net(predictions[(i-embedding):i].reshape(1,-1)).reshape(1)

        plt.plot(time.asnumpy(), x.asnumpy(), label='data');
        plt.plot(time[embedding:].asnumpy(), estimates.asnumpy(), label='estimate');
        plt.plot(time[embedding:].asnumpy(), predictions.asnumpy(), label='multistep');
        plt.legend();
```



```
In [8]: k = 33 # look up to k - embedding steps ahead
        features = nd.zeros((T-k, k))
        for i in range(embedding):
            features[:,i] = x[i:T-k+i]
        for i in range(embedding, k):
            features[:,i] = net(features[:,(i-embedding):i]).reshape((-1))
        for i in (4, 8, 16, 32):
            plt.plot(time[i:T-k+i].asnumpy(), features[:,i].asnumpy(), label=('step ' + str(i)
        plt.legend();
```


step 4
step 8
step 16
step 32
1.0
0.5
0.0
−0.5
−1.0
0
200
400
600
800
1000