digits_analysis_perceptron

June 8, 2021

1 Spoken Arabic digits perceptron analysis

This notebook contains code to reproduce the results obtained for the real dataset studied in "Covariance based information processing in reservoir computing systems" (https://doi.org/10.1101/2021.04.30.441789). To reproduce the figures presented in the paper (Fig 6 a-b, Fig 9), this code has to be adapted to run multiple times across the reservoir model space (size, leak rate, spectral radius, random seed). However, we only display results for a single reservoir configuration, to reduce computation time. Note that here we do not tune the regularization parameter when using the mean-based readout.

To reproduce results for the synthetic datasets, the same code can be used, making the corresponding changes in input data.

```
In [1]: # import libraries

        import numpy as np
        from perceptron_models import Perceptron
        from esn_models import SequentialReservoir
        import auxiliary_functions as af
        import time
        import os
        import readout_optimizers as ropt
        import pickle
        import matplotlib.pyplot as plt
```

```
In [2]: # load digits train data and zero pad it
        my_dir = os.getcwd()
        digits_train, train_labels = af.preprocess_train_data(my_dir+'/dataset/SpokenArabicDig
```

2 Working without a reservoir

We will first train mean and covariance perceptron (Perceptron class from `perceptron_models.py`) readouts directly on inputs.

In the next cell, we train the covariance perceptron using custom code.

```
In [3]: ### Create model ######

        # Initialize model
```

```python
inSize = 13
outSize = 10 # number classes
initLen = 0
trainLen = 50
non_linear = False
random_state = 42  #[42, 33, 78, 0, 91, 59, 47, 44, 40, 63] loop over this list to get
epochs = 100 # fixed
lr = 0.01 # fixed
batch_size = 32 # fixed, we can optimize it through cv grid search on training set, no

model = Perceptron(inSize=inSize, outSize=outSize, non_linear=False, random_state=rando
optimizer = ropt.GradientDescent(params=model.Wout, batch_size=batch_size, lr=lr, num_
X_train = digits_train
y_train = train_labels

# train
loss = []
np.random.seed(0)
train_scores = []
start_time = time.perf_counter()
for epoch in range(1, epochs + 1):
    # batch data, shuffle
    index = np.random.choice(X_train.shape[0], size=X_train.shape[0], replace=False)
    X_ = X_train[index, :, :]  # shuffled data
    y_ = y_train[index]  # shuffled data
    epochLoss = []
    for (batchX, batchY) in af.next_batch(X_, y_, batch_size):
        Qerror = optimizer.get_loss(batchX, batchY)
        epochLoss.append(np.sum(Qerror ** 2) / batchX.shape[0])
        delta = optimizer.get_gradients(batchX, Qerror)
        optimizer.update_params(delta)

    loss.append(np.mean(epochLoss))

    model.Wout = optimizer.params
    model.run(X_train, initLen=initLen, trainLen=trainLen, covariance=True)
    # score
    y_pred = model.predict(mode='covariance')
    score = model.score(y_train, y_pred)
    train_scores.append(score)
    print(f'Epoch {epoch} / {epochs} finished')

end_time = time.perf_counter()
print(f'Training took {end_time - start_time} seconds')
```

```
Epoch 1 / 100 finished
Epoch 2 / 100 finished
```

```
Epoch 3 / 100 finished
Epoch 4 / 100 finished
Epoch 5 / 100 finished
Epoch 6 / 100 finished
Epoch 7 / 100 finished
Epoch 8 / 100 finished
Epoch 9 / 100 finished
Epoch 10 / 100 finished
Epoch 11 / 100 finished
Epoch 12 / 100 finished
Epoch 13 / 100 finished
Epoch 14 / 100 finished
Epoch 15 / 100 finished
Epoch 16 / 100 finished
Epoch 17 / 100 finished
Epoch 18 / 100 finished
Epoch 19 / 100 finished
Epoch 20 / 100 finished
Epoch 21 / 100 finished
Epoch 22 / 100 finished
Epoch 23 / 100 finished
Epoch 24 / 100 finished
Epoch 25 / 100 finished
Epoch 26 / 100 finished
Epoch 27 / 100 finished
Epoch 28 / 100 finished
Epoch 29 / 100 finished
Epoch 30 / 100 finished
Epoch 31 / 100 finished
Epoch 32 / 100 finished
Epoch 33 / 100 finished
Epoch 34 / 100 finished
Epoch 35 / 100 finished
Epoch 36 / 100 finished
Epoch 37 / 100 finished
Epoch 38 / 100 finished
Epoch 39 / 100 finished
Epoch 40 / 100 finished
Epoch 41 / 100 finished
Epoch 42 / 100 finished
Epoch 43 / 100 finished
Epoch 44 / 100 finished
Epoch 45 / 100 finished
Epoch 46 / 100 finished
Epoch 47 / 100 finished
Epoch 48 / 100 finished
Epoch 49 / 100 finished
Epoch 50 / 100 finished
```

```
Epoch 51 / 100 finished
Epoch 52 / 100 finished
Epoch 53 / 100 finished
Epoch 54 / 100 finished
Epoch 55 / 100 finished
Epoch 56 / 100 finished
Epoch 57 / 100 finished
Epoch 58 / 100 finished
Epoch 59 / 100 finished
Epoch 60 / 100 finished
Epoch 61 / 100 finished
Epoch 62 / 100 finished
Epoch 63 / 100 finished
Epoch 64 / 100 finished
Epoch 65 / 100 finished
Epoch 66 / 100 finished
Epoch 67 / 100 finished
Epoch 68 / 100 finished
Epoch 69 / 100 finished
Epoch 70 / 100 finished
Epoch 71 / 100 finished
Epoch 72 / 100 finished
Epoch 73 / 100 finished
Epoch 74 / 100 finished
Epoch 75 / 100 finished
Epoch 76 / 100 finished
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Epoch 78 / 100 finished
Epoch 79 / 100 finished
Epoch 80 / 100 finished
Epoch 81 / 100 finished
Epoch 82 / 100 finished
Epoch 83 / 100 finished
Epoch 84 / 100 finished
Epoch 85 / 100 finished
Epoch 86 / 100 finished
Epoch 87 / 100 finished
Epoch 88 / 100 finished
Epoch 89 / 100 finished
Epoch 90 / 100 finished
Epoch 91 / 100 finished
Epoch 92 / 100 finished
Epoch 93 / 100 finished
Epoch 94 / 100 finished
Epoch 95 / 100 finished
Epoch 96 / 100 finished
Epoch 97 / 100 finished
Epoch 98 / 100 finished
```
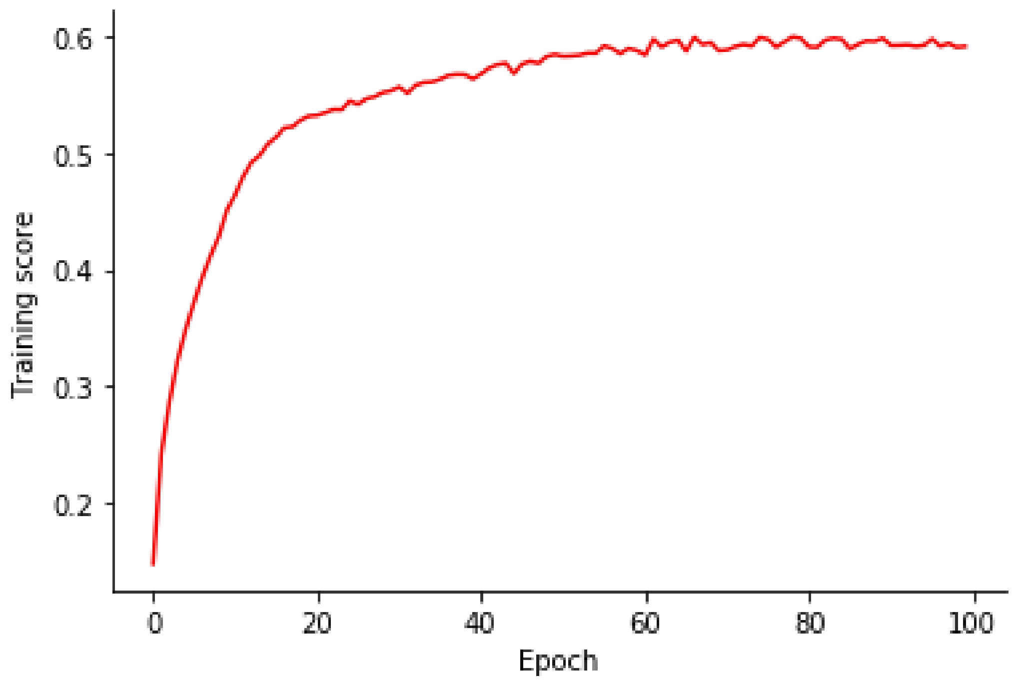

```
Epoch 99 / 100 finished
Epoch 100 / 100 finished
Training took 781.2039346 seconds
```

```
In [4]: # plot training score (or loss, up to you)
        plt.plot(np.arange(len(train_scores)), train_scores, color='r')
        plt.xlabel('Epoch')
        plt.ylabel('Training score')
        plt.show()
```




```
In [5]: # now we get test performance for our covariance perceptron model
        # load test data
        digits_test, test_labels = af.preprocess_test_data(my_dir+'/dataset/SpokenArabicDigits_
```

```
In [6]: # get test score
        model.run(digits_test, initLen=initLen, trainLen=trainLen, covariance=True)
        y_pred = model.predict(mode='covariance')
        score = model.score(test_labels, y_pred)
        print(f'Test score of final covariance perceptron model is {100*score}')
```

```
Test score of final covariance perceptron model is 59.79990904956799
```

Now we will train an example of mean-based perceptron model

```
In [7]: mean_model = Perceptron(inSize=inSize, outSize=outSize, non_linear=False, random_state=
        # train mean model
        optimizer = ropt.RidgeReg(params=mean_model.Wout, batch_size=None, solver='auto', alpha
                                  num_classes=10)

        optimizer.fit(X=X_train, y=y_train.tolist())

        # update parameters and save readout
        model.Wout = optimizer.params

        model.run(X_train, initLen=initLen, trainLen=trainLen, mean=True)

        # score
        y_pred = model.predict(mode='mean')
        print(f'Training score is {100*mean_model.score(train_labels, y_pred)}')

        # test score
        mean_model.run(digits_test, initLen=initLen, trainLen=trainLen, mean=True)
        y_pred = mean_model.predict(mode='mean')
        print(f'Test score is {100*mean_model.score(test_labels, y_pred)}')

Training score is 60.93347476890438
Test score is 58.29922692132787
```

3 Working with a reservoir

When using a reservoir in the pipeline, we simply do a "preprocessing step" where we feed the digit inputs, collect the reservoir states and afterwards use this data to train a covariance or a mean perceptron readout. As example, we will use a single reservoir of size N=50, leak=0.2 and radius = 1.2. Again, results to get figures must be ran multiple times across reservoir space parameters initialized with different random seeds. Importantly, we did not optimize the batch size for learning here, as done for the previous covariance perceptron readouts.

```
In [8]: # create reservoir
        inSize = 13 # input dimension
        resSize = 50 #reservoir size
        outsize=10 # classes
        leak = 0.2
        radius = 1.2
        random_state = 42
        initLen =  0 # collect states from beginning, no washout transient
        trainLen = 50 # this is parameter d in the paper
        reservoir = SequentialReservoir(inSize=inSize, resSize=resSize, outSize=outSize, leak=l

        # collect states
        time_start = time.perf_counter()
        reservoir.run(digits_train, initLen=initLen, trainLen=trainLen)
```

```
train_states = reservoir.resStates
time_end = time.perf_counter()
print(f'Collecting reservoir states took {time_end-time_start} seconds')
```

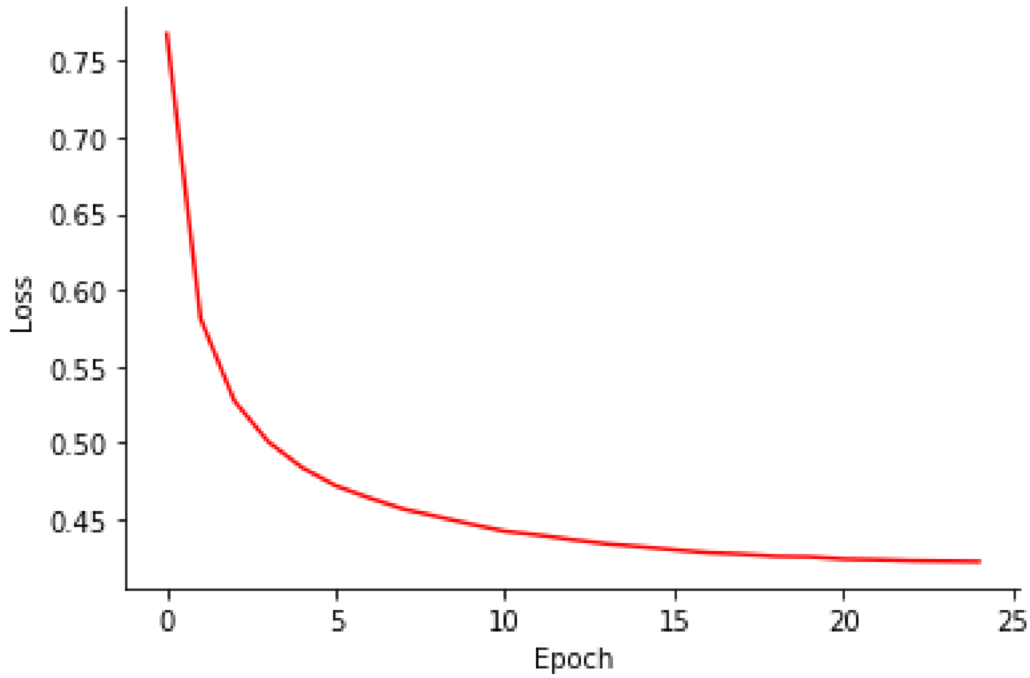
```
Collecting reservoir states took 1.6431916000000228 seconds
```

In [9]:
```
# Now train covariance model

# optimizer parameters
epochs = 25 # use 100 to get paper results
batch_size = 1 # not optimized
lr = 0.01

optimizer = ropt.GradientDescent(params=reservoir.Wout, batch_size=batch_size,
                                lr=lr, num_classes=10)

loss = []
start_time = time.perf_counter()
for epoch in range(1, epochs + 1):
    # batch data, shuffle
    index = np.random.choice(train_states.shape[0], size=train_states.shape[0], replac
    X_ = train_states[index, :, :]  # shuffled data
    y_ = train_labels[index]  # shuffled data
    epochLoss = []
    for (batchX, batchY) in af.next_batch(X_, y_, batch_size):
        Qerror = optimizer.get_loss(batchX, batchY)
        epochLoss.append(np.sum(Qerror**2)/batchX.shape[0])
        delta = optimizer.get_gradients(batchX, Qerror)
        optimizer.update_params(delta)

    loss.append(np.mean(epochLoss))
    reservoir.Wout = optimizer.params
    print(f'Epoch {epoch} / {epochs} finished')

end_time = time.perf_counter()
print(f'Training took {end_time - start_time} seconds')

# update parameters
reservoir.resStates = train_states
reservoir.update_outputs(initLen=initLen, trainLen=trainLen, covariance=True)
# score
y_pred = reservoir.predict(mode='covariance')
score = reservoir.score(train_labels, y_pred)
print(f'Training score is {100*score}')
```

```
Epoch 1 / 25 finished
Epoch 2 / 25 finished
```

```
Epoch 3 / 25 finished
Epoch 4 / 25 finished
Epoch 5 / 25 finished
Epoch 6 / 25 finished
Epoch 7 / 25 finished
Epoch 8 / 25 finished
Epoch 9 / 25 finished
Epoch 10 / 25 finished
Epoch 11 / 25 finished
Epoch 12 / 25 finished
Epoch 13 / 25 finished
Epoch 14 / 25 finished
Epoch 15 / 25 finished
Epoch 16 / 25 finished
Epoch 17 / 25 finished
Epoch 18 / 25 finished
Epoch 19 / 25 finished
Epoch 20 / 25 finished
Epoch 21 / 25 finished
Epoch 22 / 25 finished
Epoch 23 / 25 finished
Epoch 24 / 25 finished
Epoch 25 / 25 finished
Training took 990.6178782 seconds
Training score is 90.01363843006516
```

In [10]:
```
# plot training loss
plt.plot(np.arange(len(loss)), loss, color='r')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show()
```




```
In [11]: # get test score

         reservoir.run(digits_test, initLen=initLen, trainLen=trainLen)
         reservoir.update_outputs(initLen=initLen, trainLen=trainLen, covariance=True)
         # score
         y_pred = reservoir.predict(mode='covariance')
         score=reservoir.score(test_labels, y_pred)
         print(f'Test acore is {100*score}')
```

```
Test acore is 92.54206457480673
```

We will now get the digit recognition accuracy when coupling the reservoir to a mean-based perceptron readout

```
In [12]: # we will create a new reservoir so it starts from same conditions as previous one
         inSize = 13 # input dimension
         resSize = 50 #reservoir size
         outsize=10 # classes
         leak = 0.2
         radius = 1.2
         random_state = 42
         initLen =  0 # collect states from beginning, no washout transient
         trainLen = 50 # this is parameter d in the paper
         reservoir_2 = SequentialReservoir(inSize=inSize, resSize=resSize, outSize=outSize, lea
```

```
# collect states
time_start = time.perf_counter()
reservoir_2.run(digits_train, initLen=initLen, trainLen=trainLen)
train_states = reservoir_2.resStates
time_end = time.perf_counter()
print(f'Collecting reservoir states took {time_end-time_start} seconds')
```

```
Collecting reservoir states took 1.727585099999942 seconds
```

```
In [13]: # train mean model
         optimizer = ropt.RidgeReg(params=reservoir_2.Wout, batch_size=None, solver='auto', al
         optimizer.fit(X=train_states, y=train_labels.tolist())

         # update parameters and save readout
         reservoir_2.Wout = optimizer.params
         reservoir_2.update_outputs(initLen=initLen, trainLen=trainLen, mean=True)

         # score
         y_pred = reservoir_2.predict(mode='mean')
         print(f'Training score is {100*reservoir_2.score(train_labels, y_pred)}')
```

```
Training score is 86.86164570389452
```

```
In [15]: # get test score

         reservoir_2.run(digits_test, initLen=initLen, trainLen=trainLen)
         reservoir_2.update_outputs(initLen=initLen, trainLen=trainLen, mean=True)

         #score
         y_pred = reservoir_2.predict(mode='mean')
         print(f'Test score is {100*reservoir_2.score(test_labels, y_pred)}')
```

```
Test score is 86.31195998180992
```