Spike to Spike Regression: Oxford

This tutorial demonstrates *spike to spike regression* training using `lava.lib.dl.slayer`.

The task is to learn to transform a random Poisson spike train to produce output spike pattern that resembles *The Radcliffe Camera* building of Oxford University, England. The input and output both consist of 200 neurons each and the spikes span approximately 1900ms. The input and output pair are converted from SuperSpike (© GPL-3).

Input	Target
Drawing	Drawing

In [1]:
```
import os
import h5py
import numpy as np
import matplotlib.pyplot as plt
import torch
from torch.utils.data import Dataset, DataLoader

# import slayer from lava-dl
import lava.lib.dl.slayer as slayer

import IPython.display as display
from matplotlib import animation
```

Create Dataset

Create a simple PyTorch dataset class. The dataset class follows standard torch dataset definition.

It shows usage of `slayer.io` module. The module provides a way to

- easily represent events including graded spikes
- read/write events in different known binary and numpy formats
- transform event to tensor for processing it using slayer network and convert a spike tensor back to event
- display/animate the tensor for visualization

In [2]:
```
# Dear Students,

# For HW8 problem 2, please skip part 1 and instead use the below files as y
```

```
# output_hw.bs1Download output_hw.bs1

# input_hw.bs1Download input_hw.bs1

# Please update the train.ipynb notebook under slayer/oxford folder to refle

# 1. Change .bs1 files to above filenames.

# 2. Change the tensor size to (200, 600) instead of (200, 2000)



# Complete part 2 and 3 with the above changes.
```

In [ ]:

```

```

In [3]:

```
class OxfordDataset(Dataset):
    def __init__(self):
        super(OxfordDataset, self).__init__()
        self.input  = slayer.io.read_1d_spikes('input_hw.bs1' )
        self.target = slayer.io.read_1d_spikes('output_hw.bs1')
        self.target.t = self.target.t.astype(int)

    def __getitem__(self, _):
        return (
            self.input.fill_tensor(torch.zeros(1, 1, 200, 600)).squeeze(),
            self.target.fill_tensor(torch.zeros(1, 1, 200, 600)).squeeze(),
        )

    def __len__(self):
        return 1 # just one sample for this problem
```

Create Network

A slayer network definition follows standard PyTorch way using `torch.nn.Module`.

The network can be described with a combination of individual `synapse`, `dendrite`, `neuron` and `axon` components. For rapid and easy development, slayer provides **block interface** - `slayer.block` - which bundles all these individual components into a single unit. These blocks can be cascaded to build a network easily. The block interface provides additional utilities for normalization (weight and neuron), dropout, gradient monitoring and network export.

In the example below, `slayer.block.cuba` is illustrated.

In [4]:

```
class Network(torch.nn.Module):
    def __init__(self):
        super(Network, self).__init__()

        neuron_params = {
                'threshold'     : 0.1,
```

```
                'current_decay' : 1,
                'voltage_decay' : 0.1,
                'requires_grad' : True,
            }

        self.blocks = torch.nn.ModuleList([
                slayer.block.cuba.Dense(neuron_params, 200, 256),
                slayer.block.cuba.Dense(neuron_params, 256, 200),
            ])

    def forward(self, spike):
        for block in self.blocks:
            spike = block(spike)
        return spike

    def export_hdf5(self, filename):
        # network export to hdf5 format
        h = h5py.File(filename, 'w')
        layer = h.create_group('layer')
        for i, b in enumerate(self.blocks):
            b.export_hdf5(layer.create_group(f'{i}'))
```

Instantiate Network, Optimizer, DataSet and DataLoader

Running the network in GPU is as simple as selecting `torch.device('cuda')`.

In [5]:
```
trained_folder = 'Trained'
os.makedirs(trained_folder, exist_ok=True)

device = torch.device('cpu')
# device = torch.device('cuda')

net = Network().to(device)

optimizer = torch.optim.Adam(net.parameters(), lr=0.001, weight_decay=1e-5)

training_set = OxfordDataset()
train_loader = DataLoader(dataset=training_set, batch_size=1)
```

Visualize the input and output spike train

A `slayer.io.Event` can be visualized by invoking it's `Event.show()` routine. `Event.anim()` instead returns the event visualization animation which can be embedded in notebook or exported as video/gif. Here, we will export gif animation and visualize it.

In [6]:
```
input_anim  = training_set.input.anim(plt.figure(figsize=(10, 10)))
target_anim = training_set.target.anim(plt.figure(figsize=(10, 10)))
```

```python
## This produces interactive animation
# display.HTML(input_anim.to_jshtml())
# display.HTML(target_anim.to_jshtml())

## Saving and loading gif for better animation in github
input_anim.save('input.gif', animation.PillowWriter(fps=24), dpi=300)
target_anim.save('target.gif', animation.PillowWriter(fps=24), dpi=300)
```

In [7]:

```python
gif_td = lambda gif: f'<td> <img src="{gif}" alt="Drawing" style="height: 40
html = '<table><tr>'
html += '<td> Input </td><td> Target </td></tr><tr>'
html += gif_td(f'input.gif')
html += gif_td(f'target.gif')
html += '</tr></table>'
display.HTML(html)
```

Out[7]:

Input	Target
Drawing	Drawing

Error module

Slayer provides prebuilt loss modules: `slayer.loss.{SpikeTime, SpikeRate, SpikeMax}`.

- `SpikeTime` : precise spike time based loss when target spike train is known.
- `SpikeRate` : spike rate based loss when desired rate of the output neuron is known.
- `SpikeMax` : negative log likelihood losses for classification without any rate tuning.

Since the target spike train $\hat{\boldsymbol{s}}(t)$ is known for this problem, we use `SpikeTime` loss here. It uses *van Rossum* like spike train distance metric. The actual and target spike trains are filtered using a FIR filter and the norm of the timeseries is the loss metric.

$$L = \frac{1}{2T}\int_T \left(h_{\text{FIR}} * (\boldsymbol{s} - \hat{\boldsymbol{s}})\right)(t)^\top \mathbf{1}\,\text{d}t$$

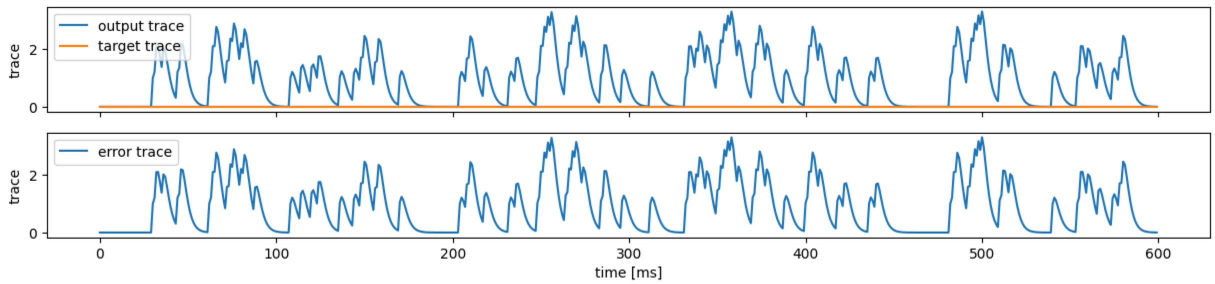
- `time_constant` : time constant of the FIR filter.
- `filter_order` : the order of FIR filter. Exponential decay is first order filter.

In [8]:

```python
error = slayer.loss.SpikeTime(time_constant=2, filter_order=2).to(device)

# the followng portion just illustrates the SpikeTime loss calculation.
# IT IS NOT NEEDED IN PRACTICE
input, target = training_set[0]
output = net(input.unsqueeze(dim=0).to(device))[0]
# just considering first neuron for illustration
output_trace = error.filter(output[0].to(device)).flatten().cpu().data.numpy
target_trace = error.filter(target[0].to(device)).flatten().cpu().data.numpy
```

```
fig, ax = plt.subplots(2, 1, figsize=(15, 3), sharex=True)
ax[0].plot(output_trace, label='output trace')
ax[0].plot(target_trace, label='target trace')
ax[1].plot(output_trace - target_trace, label='error trace')
ax[0].set_ylabel('trace')
ax[1].set_ylabel('trace')
ax[1].set_xlabel('time [ms]')
for a in ax: a.legend()
```



Stats and Assistants

Slayer provides `slayer.utils.LearningStats` as a simple learning statistics logger for training, validation and testing.

In addtion, `slayer.utils.Assistant` module wraps common training validation and testing routine which help simplify the training routine.

In [9]:
```
stats = slayer.utils.LearningStats()
assistant = slayer.utils.Assistant(net, error, optimizer, stats)
```

Training Loop

Training loop mainly consists of looping over epochs and calling `assistant.train` utility to train.

- `stats` can be used in print statement to get formatted stats printout.
- `stats.training.best_loss` can be used to find out if the current iteration has the best loss. Here, we use it to save the best model.
- `stats.update()` updates the stats collected for the epoch.
- `stats.save` saves the stats in files.

In [10]:
```
epochs = 2000

for epoch in range(epochs):
    for i, (input, target) in enumerate(train_loader): # training loop
        output = assistant.train(input, target)
        print(f'\r[Epoch {epoch:3d}/{epochs}] {stats}', end='')

    if stats.training.best_loss:
```

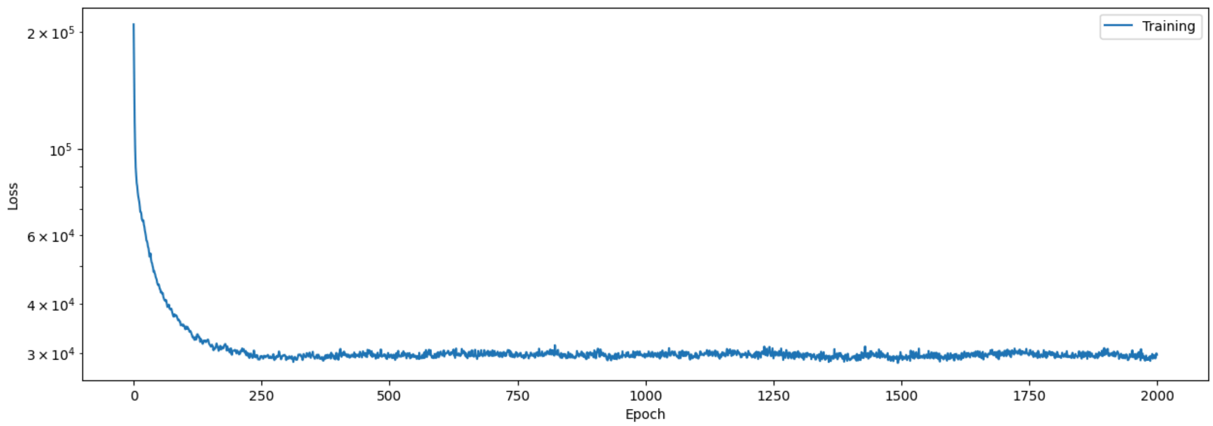
```
        torch.save(net.state_dict(), trained_folder + '/network.pt')
    stats.update()
    stats.save(trained_folder + '/')
```

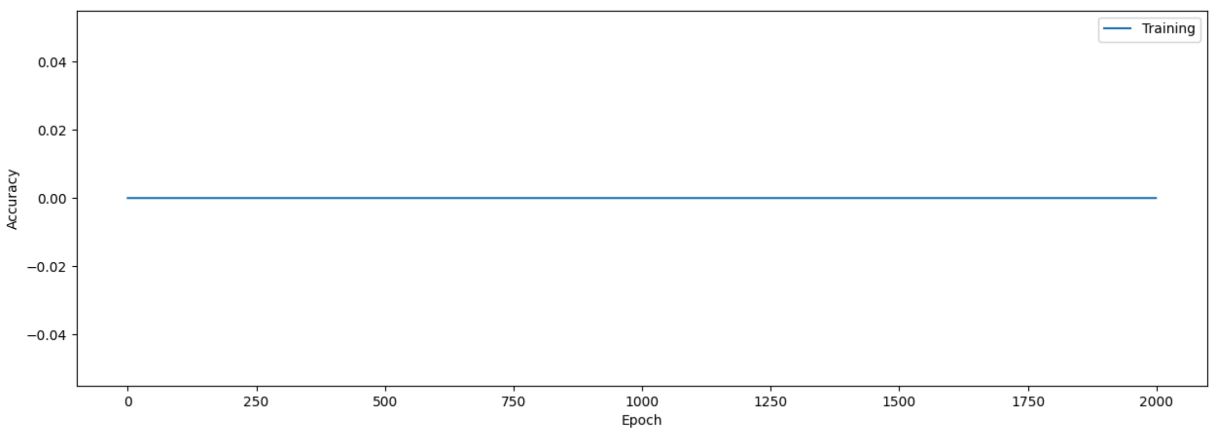
```
[Epoch 1999/2000] Train loss = 29628.36133 (min = 28220.17188)     accuracy
= 0.00000 (max = 0.00000)
```

Plot the learning curves

Plotting the learning curves is as easy as calling `stats.plot()`.

In [11]:
```
stats.plot(figsize=(15, 5))
```





Export the best model

Load the best model during training and export it as hdf5 network. It is supported by `lava.lib.dl.netx` to automatically load the network as a lava process.

In [12]:
```
net.load_state_dict(torch.load(trained_folder + '/network.pt'))
net.export_hdf5(trained_folder + '/network.net')
```

Visualize the network output

Here, we will use `slayer.io.tensor_to_event` method to convert the torch output spike tensor into `slayer.io.Event` object and visualize the input and output event.

In [13]:
```
output = net(input.to(device))
event = slayer.io.tensor_to_event(output.cpu().data.numpy())
output_anim = event.anim(plt.figure(figsize=(10, 10)))
# display.HTML(output_anim.to_jshtml())
output_anim.save('output.gif', animation.PillowWriter(fps=24), dpi=300)

html = '<table><tr>'
html += '<td>Output</td><td>Target</td></tr><tr>'
html += gif_td(f'output.gif')
html += gif_td(f'target.gif')
html += '</tr></table>'
display.HTML(html)
```

Out[13]:

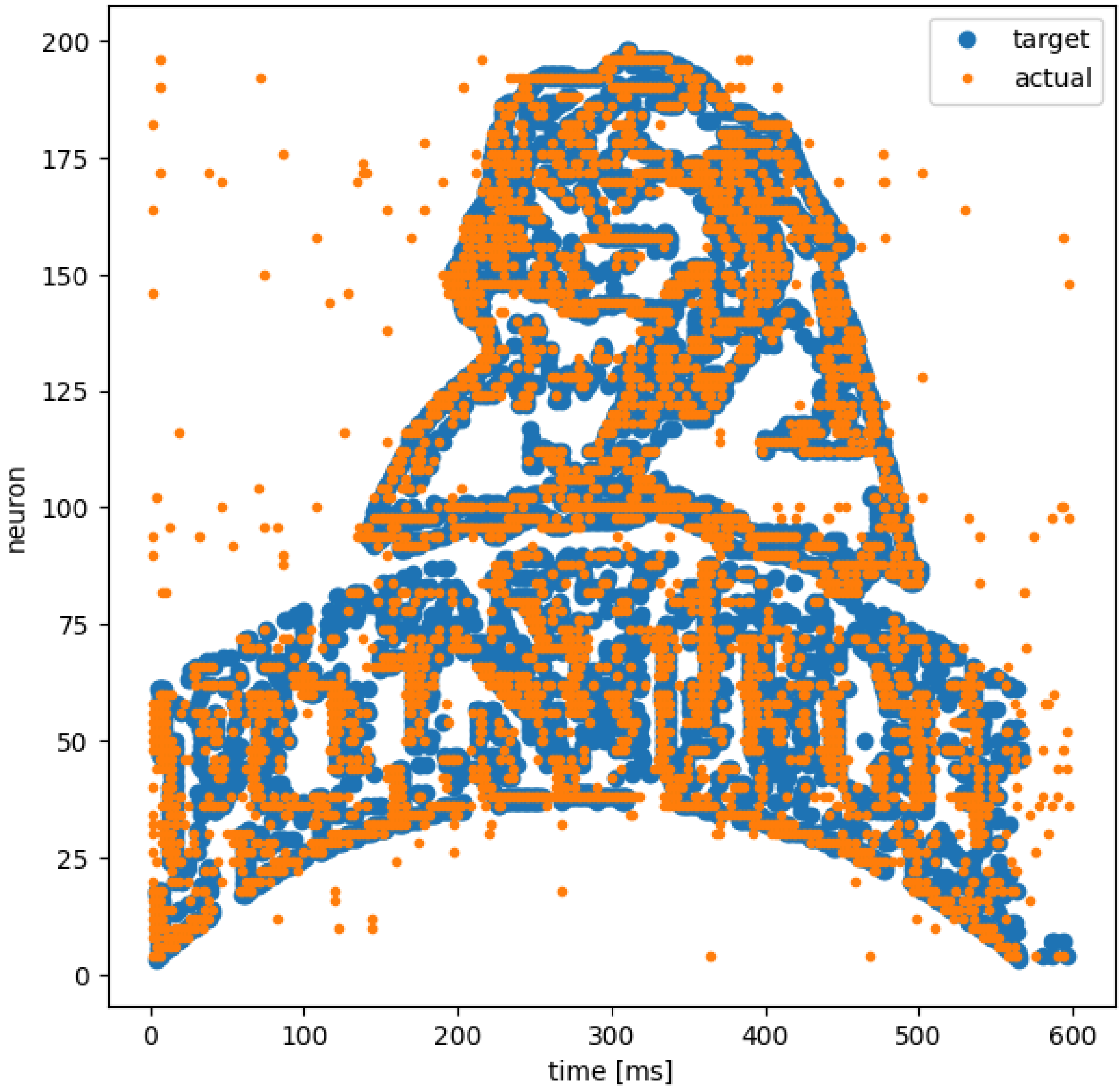
Output	Target
Drawing	Drawing

Compare Output vs Target

Event data can be accessed as `slayer.io.Event.{x, y, c, t, p}` for x-address, y-address, channel-address, timestamp and graded-payload. This can be used for further processing and visualization of event data.

In [14]:
```
plt.figure(figsize=(7, 7))
plt.plot(training_set.target.t, training_set.target.x, '.', markersize=12, l
plt.plot(event.t, event.x, '.', label='actual')
plt.xlabel('time [ms]')
plt.ylabel('neuron')
plt.legend()
```

Out[14]:
```
<matplotlib.legend.Legend at 0x16aa2adf0>
```



The target is similar to the original and actual image. There is some data loss, but overall the spike to spike regression has performed very well at creating lines in the image above and has filled in spots where there were curves in the image.