```
In [ ]: import DW_oscillator as DW
        import numpy as np
        from IPython.display import clear_output
        from torchdiffeq import odeint
        import torch
        import torch.nn as nn
        import torch.optim as optim
        from torch.nn import functional as F
        import matplotlib.pyplot as plt
In [ ]: def DW_EoM(t, y, params):
            DW oscillator equation of motion
            Parameters
            _____
            t : time
            y : array containing the DW position and angle
            params : DW class object containing all the parameter functions
            Returns
            -----
            gradient: array of equation of motion
            x, phi = y
            Bx, Bphi = params.fields(x, phi, t)
            dx = params.DW_width(phi)*params.beta*(params.alpha * Bx - Bphi)
            dphi = params.beta*(params.alpha*Bphi + Bx)
            return [dx, dphi]
In [ ]: class field_sequence:
            callable class to produce a time dependent field sequence
            def __init__ (self, fields, periods):
                import numpy as np
                self.fields = fields
                self.periods = periods
                self.periods_sum = np.cumsum(periods)
            def __call__ (self, t):
                if t < 0.0:
                    val = 0.0
                elif t >= self.periods_sum[-1]:
                    val = 0.0
                else:
                    t_diff = self.periods_sum - t
                    n = 0
                    for i in range(len(t_diff)):
                        if t_diff[i] >= 0.0:
                            n = i
                            break
```

```
val = self.fields[n]
return val
```

```
In [ ]: def run_field_sequence(field_low = 0.0, field_high = 1000.0, N_fields = 10, T = 4,
            from scipy.integrate import solve_ivp
            rng = np.random.default_rng()
            fields = rng.uniform(field_low, field_high, N_fields)
            periods = np.ones(len(fields))*T
            total_time = np.sum(periods)
            print(fields)
            print(periods)
            htime = field_sequence(fields, periods)
            dw1 = DW(477e3, 1.05e-11, 0.02, (600e-9, 50e-9, 5e-9), -1.28e-6, 1.63e8, 0.0, 0
            t_eval = np.arange(0, total_time, dt)
            sol = solve_ivp( DW_EoM, [0, total_time], y0, args=[dw1], t_eval=t_eval)
            h_vals = np.zeros_like(sol.t)
            for i in range(len(h_vals)):
                h_vals[i] = dw1.Happ(t_eval[i])
            return sol.t, sol.y, h_vals, fields, periods
```

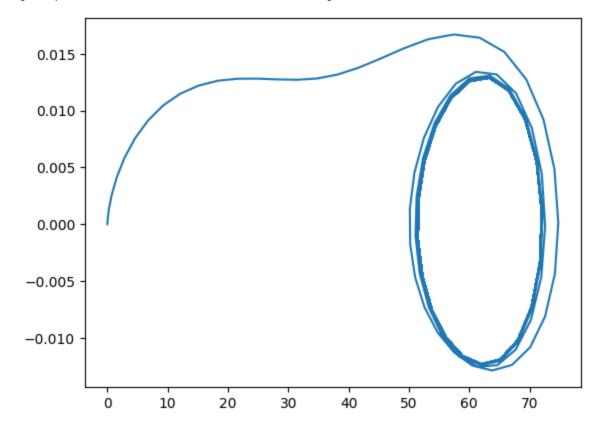
"run\_field\_sequence" that randomly generates and simulates a set of fields. It returns the time, DW position and angle plus the input time sequence. field\_low and field\_high specify the range the fields will be generated over while N\_fields is the number of fields in the sequence and T is the time period of each field.

The outputs of interest are t, y and h\_t. y[0] is the DW position over time (at time points given in t) and h\_t is the magnetic field (serves as input) at the same times.

```
class DWODE(nn.Module):
In [ ]:
            neural network for learning the chaotic lorenz system
            def __init__(self):
                 super(DWODE, self).__init__()
                 self.lin = nn.Linear(3, 64)
                 self.lin2 = nn.Linear(64, 128)
                 self.lin3 = nn.Linear(128, 256)
                 self.lin4 = nn.Linear(256,3)
                 self.relu = nn.ReLU()
            def forward(self, t,x):
                x = self.relu(self.lin(x))
                x = self.relu(self.lin2(x))
                x = self.relu(self.lin3(x))
                x = self.lin4(x)
                 return x
```

```
In [ ]: plt.plot(y[0],y[1])
```

Out[ ]: [<matplotlib.lines.Line2D at 0x15a312a0340>]

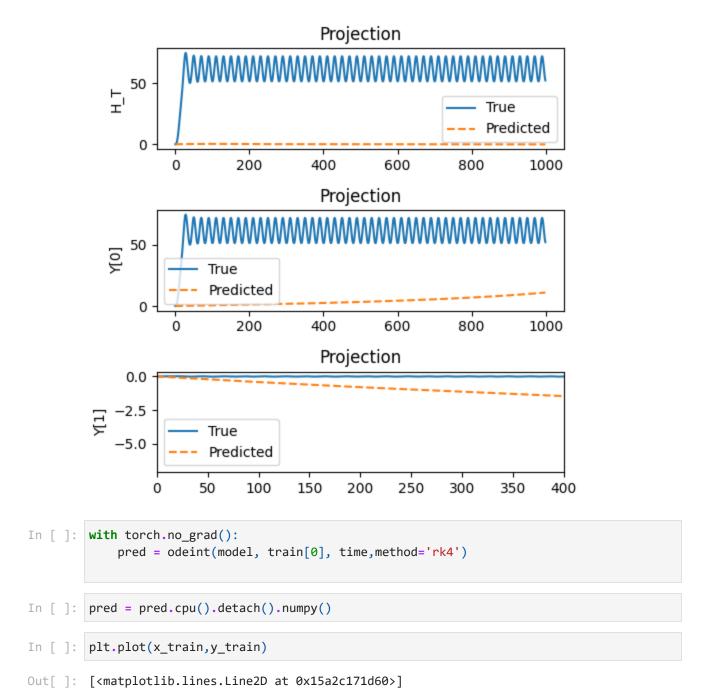


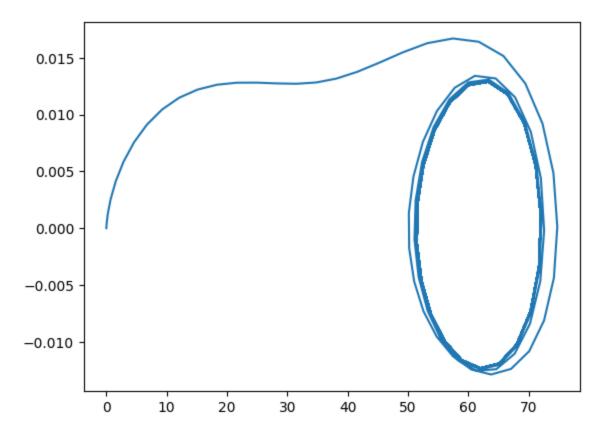
```
In [ ]: y.shape
Out[ ]: (2, 100)
In [ ]: time = torch.tensor(t).to(device)
```

```
In [ ]: h_t_ = torch.tensor(h_t, dtype=torch.float64) # Converting to column vector
        y_0_ = torch.tensor(y[0], dtype=torch.float64) # Converting to column vector
        y_1_ = torch.tensor(y[1], dtype=torch.float64) # Converting to column vector
        # Stack the tensors horizontally
        train = torch.stack((h_t_,y_0_, y_1_)).to(device)
In [ ]: train.shape
Out[]: torch.Size([3, 1000])
In [ ]: train = train.transpose(0,1)
In [ ]: train.shape
Out[]: torch.Size([1000, 3])
In [ ]: model = DWODE().double().to(device)
In [ ]: optimizer = optim.Adam(model.parameters(), lr=1e-6,weight_decay=1e-4)
In [ ]: def get_batch(true_y, batch_size):
            num samples = len(true y)
            indices = np.random.choice(np.arange(num_samples - batch_size, dtype=np.int64),
            indices.sort()
            #print(indices)
            batch_y0 = true_y[indices] # (batch_size, D)
            batch_t = time[:batch_size] # (batch_size)
            batch_y = torch.stack([true_y[indices + i] for i in range(batch_size)], dim=0)
            return batch_y0,batch_t,batch_y
In [ ]: for i in range(4000):
            optimizer.zero_grad()
            init,batch_t,truth = get_batch(train,20)
            #print(init,batch_t,truth)
            pred_y = odeint(model,init,batch_t)
            loss = F.mse_loss(pred_y, truth)
            loss.backward()
            optimizer.step()
            if i % 100 == 0:
                with torch.no_grad():
                    pred_y = odeint(model, train[0], time)
                    loss = F.mse_loss(pred_y, train)
                    print('Iter {:04d} | Total Loss {:.6f}'.format(i, loss.item()))
                    x_pred = pred_y[:,0].cpu()
                    y_pred = pred_y[:,1].cpu()
                    z_pred = pred_y[:,2].cpu()
```

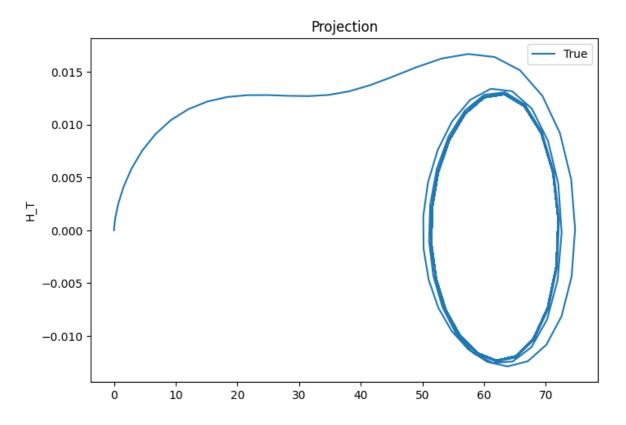
```
# Extract the x, y, z coordinates from X_train_plt
x_train = train[:,0].cpu()
y_train = train[:,1].cpu()
z_train = train[:,2].cpu()
fig, ax = plt.subplots(3, 1, figsize=(5, 5))
ax[0].plot(y[0], label='True')
ax[0].plot(x_pred, label='Predicted', linestyle='--')
ax[0].set_ylabel('H_T')
ax[0].set_title('Projection')
ax[0].legend()
ax[1].plot(y_train, label='True')
ax[1].plot(y_pred, label='Predicted',linestyle='--')
ax[1].set_ylabel('Y[0]')
ax[1].set_title('Projection')
ax[1].legend()
ax[2].plot(z_train, label='True')
ax[2].plot(z_pred, label='Predicted',linestyle='--')
ax[2].set_ylabel('Y[1]')
ax[2].set_xlim(0, 400)
ax[2].set_title('Projection')
ax[2].legend()
plt.tight_layout()
plt.show()
clear_output(wait=True)
```

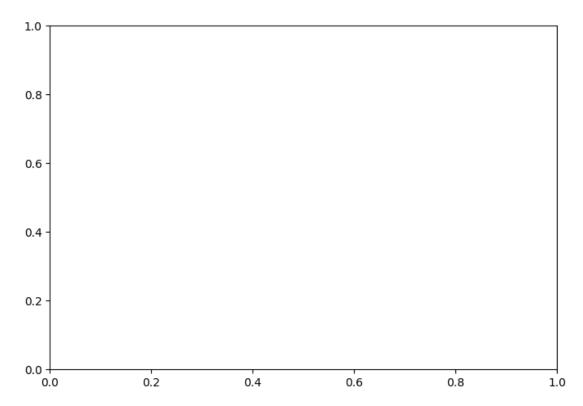
Iter 3900 | Total Loss 2767.016241





```
In []: fig, ax = plt.subplots(2, 1, figsize=(8, 12))
    ax[0].plot(y[0], y[1], label='True')
    #ax[0].plot(x_pred, y_pred, label='Predicted', linestyle='--')
    ax[0].set_ylabel('H_T')
    ax[0].set_title('Projection')
    ax[0].legend()
    plt.show()
```

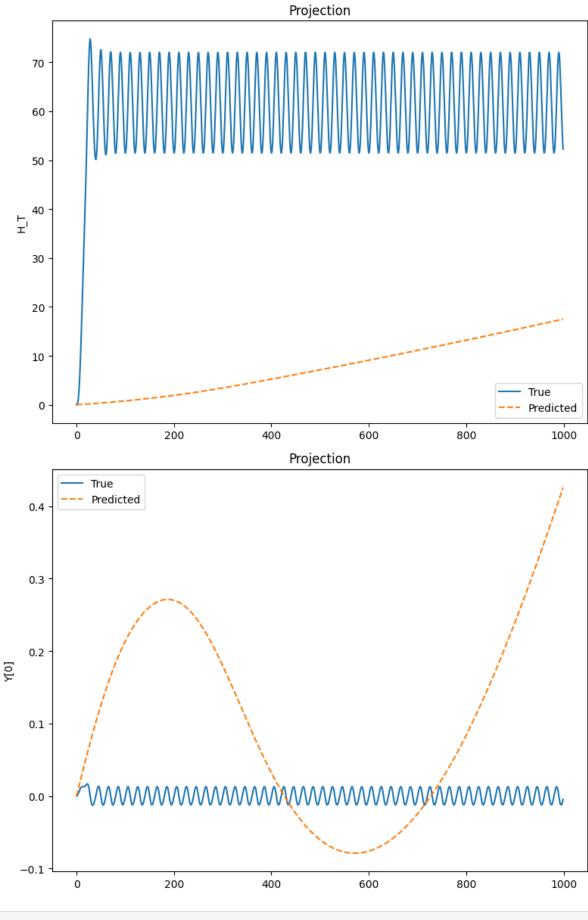




```
In []: # Extract the x, y, z coordinates from predictions_plt
x_pred = pred[:,0]
y_pred = pred[:,1]

# Extract the x, y, z coordinates from X_train_plt
x_train = train[:,0].cpu()
```

```
y_train = train[:,1].cpu()
fig, ax = plt.subplots(2, 1, figsize=(8, 12))
ax[0].plot(x_train, label='True')
ax[0].plot(x_pred, label='Predicted',linestyle='--')
ax[0].set_ylabel('H_T')
# ax[0].set_xlim(0, 200)
# ax[0].set_ylim(0, 300)
ax[0].set_title('Projection')
ax[0].legend()
ax[1].plot(y_train, label='True')
ax[1].plot(y_pred, label='Predicted',linestyle='--')
ax[1].set_ylabel('Y[0]')
ax[1].set_title('Projection')
ax[1].legend()
# ax[2].plot(z_train, label='True')
# ax[2].plot(z_pred, label='Predicted', linestyle='--')
# ax[2].set_ylabel('Y[1]')
#ax[2].set_xlim(0, 400)
# ax[2].set_title('Projection')
# ax[2].Legend()
plt.tight_layout()
plt.show()
```



In [ ]: plt.plot(x\_pred)

Out[ ]: [<matplotlib.lines.Line2D at 0x15a2a860b80>]

