In [1]:
```
# these are some necessary libs, but feel free to import whatever you need
import torch
import torch.nn as nn
import torch.nn.functional as F
import numpy as np
from matplotlib import pyplot as plt
import math
```

In [2]:
```
### don't change this
### seed everything for reproducibility
def seed_everything():
    seed = 42
    np.random.seed(seed)
    torch.manual_seed(seed)
    torch.cuda.manual_seed(seed)
```

2. Prepare for the Transformer

2(a) Implement a scaled dot product

In [3]:
```
def scaled_dot_product(q, k, v):
    d_k = q.size()[-1]

    # TODO: put your code below
    # values should be the final output
    # attention should be the n by n attention matrix (the dot product after softmax)


    scores = torch.matmul(q, k.transpose(-2, -1))
    scores = scores/math.sqrt(d_k)

    attention = F.softmax(scores, dim=-1)

    values = torch.matmul(attention, v)

    #========================#
    return values, attention
```

In [4]:
```
### set what you get
### do not modify this cell
seed_everything()
seq_len, d_k = 3, 2
q = torch.randn(seq_len, d_k)
k = torch.randn(seq_len, d_k)
v = torch.randn(seq_len, d_k)
values, attention = scaled_dot_product(q, k, v)
print("Q\n", q)
print("K\n", k)
print("V\n", v)
print("Values\n", values)
print("Attention\n", attention)
assert attention.shape == (seq_len, seq_len)
```

```
Q
 tensor([[ 0.3367,  0.1288],
        [ 0.2345,  0.2303],
        [-1.1229, -0.1863]])
K
 tensor([[ 2.2082, -0.6380],
        [ 0.4617,  0.2674],
        [ 0.5349,  0.8094]])
V
 tensor([[ 1.1103, -1.6898],
        [-0.9890,  0.9580],
        [ 1.3221,  0.8172]])
Values
 tensor([[ 0.5698, -0.1520],
        [ 0.5379, -0.0265],
        [ 0.2246,  0.5556]])
Attention
 tensor([[0.4028, 0.2886, 0.3086],
        [0.3538, 0.3069, 0.3393],
        [0.1303, 0.4630, 0.4067]])
```

2(b) Try masked scaled-dot product

In [5]:
```python
def masked_scaled_dot_product(q, k, v, mask):
    # the mask will be in shape n by n, it indicates the interaction between specific pair of tokens need not be considered
    d_k = q.size()[-1]

    # TODO: put your code below
    # values should be the final output
    # attention should be the n by n attention matrix (the dot product after softmax)

    scores = torch.matmul(q, k.transpose(-2, -1))
    scores = scores/math.sqrt(d_k)

    attention = F.softmax(scores.masked_fill_(mask, 1e-9), dim=-1)

    values = torch.matmul(attention, v)

    #=======================#
    return values, attention
```

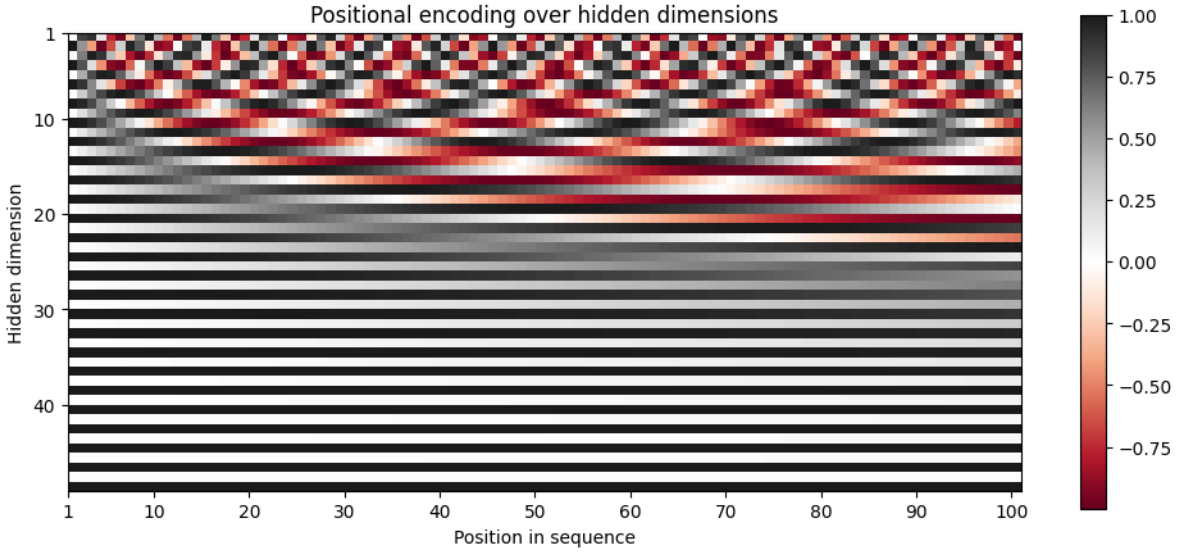
In [6]:
```python
### set what you get
### do not modify this cell
seed_everything()
seq_len, d_k = 3, 2
# create a low triangular mask
# looks like this
# 1 0 0
# 1 1 0
# 1 1 1
# this will also be helpful for masked attention in the decoder
mask = torch.tril(torch.ones(seq_len, seq_len)) == 0
q = torch.randn(seq_len, d_k)
k = torch.randn(seq_len, d_k)
v = torch.randn(seq_len, d_k)
values, attention = masked_scaled_dot_product(q, k, v, mask)
print("Q\n", q)
print("K\n", k)
print("V\n", v)
print("Values\n", values)
print("Attention\n", attention)
```

```
Q
 tensor([[ 0.3367,  0.1288],
        [ 0.2345,  0.2303],
        [-1.1229, -0.1863]])
K
 tensor([[ 2.2082, -0.6380],
        [ 0.4617,  0.2674],
        [ 0.5349,  0.8094]])
V
 tensor([[ 1.1103, -1.6898],
        [-0.9890,  0.9580],
        [ 1.3221,  0.8172]])
Values
 tensor([[ 0.5855, -0.2564],
        [ 0.4815, -0.0872],
        [ 0.2246,  0.5556]])
Attention
 tensor([[0.4439, 0.2781, 0.2781],
        [0.3792, 0.3290, 0.2918],
        [0.1303, 0.4630, 0.4067]])
```

2(c) Positional encoding (from original Transformer)

In [7]:
```python
class PositionalEncoding(nn.Module):

    def __init__(self, d_model, max_len=5000):
        """
        Inputs
            d_model - Hidden dimensionality of the input.
            max_len - Maximum length of a sequence to expect.
        """
        super().__init__()

        # Create matrix of [SeqLen, HiddenDim] representing the positional encoding for max_len inputs
        pe = torch.zeros(max_len, d_model)

        # ================================== #
        # TODO: put your code below
        pos = torch.arange(0, max_len, dtype=torch.float).unsqueeze(dim=1)

        i = torch.arange(0, d_model, step=2, dtype=torch.float)

        pe[:, 0::2] = torch.sin(pos / (10000 ** (i/d_model)))
        pe[:, 1::2] = torch.cos(pos / (10000 ** (i/d_model)))
        # ================================== #
        # register_buffer => Tensor which is not a parameter, but should be part of the modules state.
        # Used for tensors that need to be on the same device as the module.
        # persistent=False tells PyTorch to not add the buffer to the state dict (e.g. when we save the model)
        self.register_buffer('pe', pe, persistent=False)

    def forward(self, x):
        pe = self.pe[:x.size(1), :]

        #TODO: put your code below

        return pe
```

In [8]:
```
### visualize the positional encoding and see what you get, do not modify this

pe_block = PositionalEncoding(d_model=48, max_len=100)
pe = pe_block.pe.squeeze().T.cpu().numpy()

fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(12,5))
pos = ax.imshow(pe, cmap="RdGy", extent=(1,pe.shape[1]+1,pe.shape[0]+1,1))
fig.colorbar(pos, ax=ax)
ax.set_xlabel("Position in sequence")
ax.set_ylabel("Hidden dimension")
ax.set_title("Positional encoding over hidden dimensions")
ax.set_xticks([1]+[i*10 for i in range(1,1+pe.shape[1]//10)])
ax.set_yticks([1]+[i*10 for i in range(1,1+pe.shape[0]//10)])
plt.show()
```



3. Build your own "GPT" for 1D Burgers' prediction

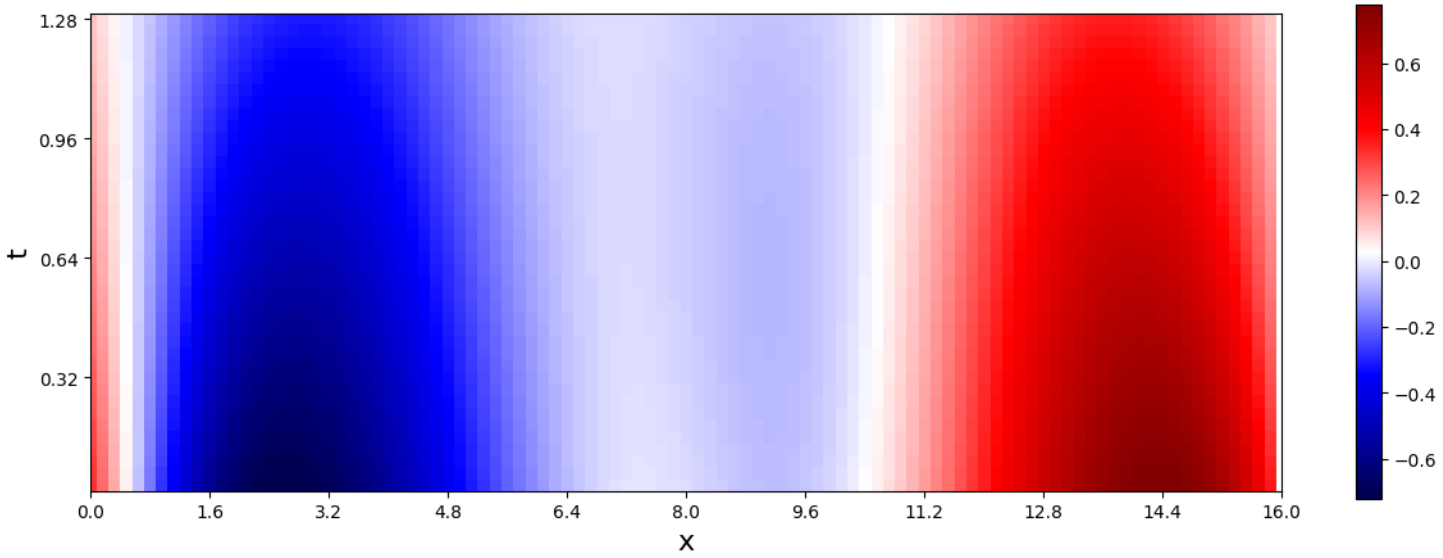
In [9]:
```
from google.colab import drive
drive.mount('/content/drive')

data_path = '/content/drive/MyDrive/24788-24789/24789-hw4-attention/'

### load data, modify this when you have a different path
train_data = np.load(data_path+'burgers_train.npy')
test_data = np.load(data_path+'burgers_test.npy')
print(train_data.shape, test_data.shape)
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
(2048, 40, 100) (128, 40, 100)
```

Visualize a sequence (optional)

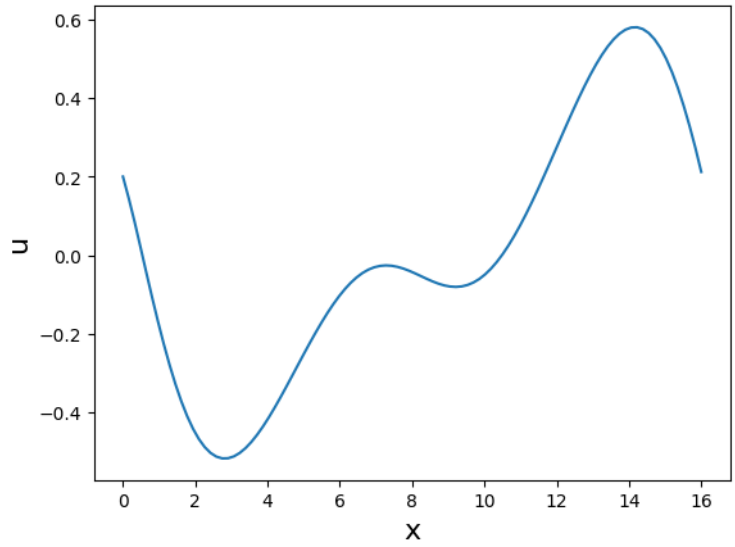
In [10]:
```
### You don't have to modify this function
from matplotlib.ticker import FormatStrFormatter

def show_field(field):

    fig, ax = plt.subplots(figsize=(15, 5))
    # mark y axis as time, x axis as space
    ax.set_xlabel('x',fontsize=16)
    ax.set_ylabel('t', fontsize=16)
    ax.set_xlim(0, 50+1e-5)

    ax.set_yticks(np.arange(0, 41, 10), [str(round(f, 2)) for f in np.linspace(0, 1.28, 5)][::-1])
    ax.set_xticks(np.arange(0, 101, 10),[str(round(f, 2)) for f in np.linspace(0, 16, 11)])

    im = ax.imshow(field,cmap='seismic')
    plt.colorbar(im)

    plt.show()
```

In [11]:
```
show_field(train_data[0])
```



In [12]:
```
# take a look at one of the snapshots
plt.plot(np.linspace(0, 16, 100), train_data[0, 20])
plt.gca().set_xlabel('x',fontsize=16)
plt.gca().set_ylabel('u', fontsize=16)
```

Out[12]: `Text(0, 0.5, 'u')`



Helper functions (do not modify!)

In [13]:
```python
### do not modify this cell
### ======================
class SimpleEncoder(nn.Module):
    # for embedding the first 10 time steps of darcy flow
    def __init__(self,
                 input_dim=100,    # we take number of grid points as number of feature for each frame
                 hidden_dim=64,   # hidden dimensionality of the encoder
                 emb_dim=128):
        super().__init__()
        # we use 1d depth-wise convolution to embed the input
        self.net = nn.Sequential(
            nn.Conv1d(input_dim, hidden_dim, kernel_size=1, stride=1, padding=0, groups=4),
            nn.GELU(),   # GELU is a better version of ReLU, for most tasks
            nn.Conv1d(hidden_dim, hidden_dim, kernel_size=1, stride=1, padding=0, groups=8),
            nn.GELU(),
            nn.Conv1d(hidden_dim, hidden_dim, kernel_size=1, stride=1, padding=0, groups=4),
            nn.GELU(),
            nn.Conv1d(hidden_dim, hidden_dim, kernel_size=1, stride=1, padding=0),
            nn.GELU(),
            nn.Conv1d(hidden_dim, emb_dim, kernel_size=1, stride=1, padding=0))

        self.to_out = nn.Sequential(
            nn.LayerNorm(emb_dim),
            nn.Linear(emb_dim, emb_dim),
        )

    def forward(self, x):
        # x will be in shape [b t n], n is number of grid points, but you can think it as feature dimension
        # we need to transpose it to [b n t] for the convolution
        x = x.transpose(1, 2)
        # now we can apply the convolution
        x = self.net(x)
        x = x.transpose(1, 2)
        return self.to_out(x)


class SimpleDecoder(nn.Module):
    # go back from the latent space to the physical space
    def __init__(self,
                 input_dim=128,     # latent dimensionality
                 hidden_dim=64,   # hidden dimensionality of the decoder
                 output_dim=100):
        super().__init__()
        self.ln = nn.LayerNorm(input_dim)
        self.net = nn.Sequential(
            nn.Conv1d(input_dim, hidden_dim, kernel_size=1, stride=1, padding=0),
            nn.GELU(),
            nn.Conv1d(hidden_dim, hidden_dim, kernel_size=1, stride=1, padding=0, groups=4),
            nn.GELU(),
            nn.Conv1d(hidden_dim, output_dim, kernel_size=1, stride=1, padding=0, groups=2),
        )

    def forward(self, x):
        # x will be in shape [b t c]
        x = self.ln(x)
        x = x.transpose(1, 2)
        x =  self.net(x).transpose(1, 2)  # [b t c] again
        return x



class FFN(nn.Module):
    # give to you for free, need to be used in the transformer
    def __init__(self, input_dim=128, hidden_dim=128, output_dim=128):
        super().__init__()
        self.net = nn.Sequential(
            nn.LayerNorm(input_dim),
            nn.Linear(input_dim, hidden_dim),
            nn.GELU(),
            nn.Linear(hidden_dim, output_dim),
        )

    def forward(self, x):
        return self.net(x)
```

Implement a multi-head self-attention module (with causal mask)

In [14]:
```python
# you need to implement this
class CausalSelfAttention(nn.Module):

    def __init__(self,
                 dim,
                 dim_head,
                 num_heads,
                 dropout,       # dropout for attention matrix (Q^T K), not input or output
                 max_len=50
                 ):
        super().__init__()
        self.dim = dim
        self.inner_dim = dim_head * num_heads
        self.num_heads = num_heads
        self.dim_head = dim_head

        mask = torch.tril(torch.ones(max_len, max_len)) == 0
        self.mask = mask.cuda()
        # ================================================================
        #TODO: implement the module of the causal self attention
        self.w_qkv = nn.Linear(self.dim, 3*self.inner_dim)
        self.w_o = nn.Linear(self.inner_dim, self.dim)

        self.dropout = nn.Dropout(dropout)




        # ================================================================
        self._init_weights()

    def _init_weights(self):
        # you can implement some weight initialization here (optional), can provide some performance boost when doing it correctly
        nn.init.xavier_uniform_(self.w_qkv.weight)
        self.w_qkv.bias.data.fill_(0)

        nn.init.xavier_uniform_(self.w_o.weight)
        self.w_o.bias.data.fill_(0)

    def forward(self, x):
        # input is in shape [b t c], output is also in shape [b t c]
        B, L, C = x.size() # batch size, sequence length, embedding dimensionality (n_embd)

        # ================================================================
        #TODO: implement the forward pass of the causal self attention

        qkv = self.w_qkv(x)
        qkv = qkv.reshape(B, L, self.num_heads, 3*self.dim_head) # Split split dimension into each head
        qkv = qkv.permute(0, 2, 1, 3) # [batch size, number of heads, sequence length, head dimensions]
        q, k, v = qkv.chunk(3, dim=-1) # separate query, key and value matrices

        _, attention = masked_scaled_dot_product(q, k, v, self.mask[:L,:L])

        attention = self.dropout(attention)
        values = torch.matmul(attention, v)

        values = values.permute(0, 2, 1, 3) # [batch size, sequence length, number of heads, head dimensions]
        values = values.reshape(B, L, self.inner_dim) # [batch size, sequence length, inner dimension]

        out = self.w_o(values)

        return out
```

Use above attention block to build a PDE-GPT

In [15]:
```python
### you only have to fill a small part inside the forward function
class PDEGPT(nn.Module):
    def __init__(self,
                 num_layers,    # the only hyperparameter to play with, could start with sth like 6
                 ):
        super().__init__()

        self.transformer = nn.ModuleList([])
        for _ in range(num_layers):
            self.transformer.append(nn.ModuleList([
                nn.LayerNorm(128),
                CausalSelfAttention(dim=128, dim_head=128, num_heads=4, dropout=0.05),
                FFN(input_dim=128, hidden_dim=128, output_dim=128),
            ]))
        self.function_encoder = SimpleEncoder()
        self.function_decoder = SimpleDecoder()
        self.position_embedding =  PositionalEncoding(128, 40)

        # report number of parameters
        print(f"Total number of trainable parameters: {self.get_num_params()}" )

    def get_num_params(self):
        n_params = sum(p.numel() for p in self.parameters() if p.requires_grad)
        return n_params

    def forward(self, seq, noise=True, tstart=0):
        # seq in shape [batch_size, 49, 100] t=49, n=100, think about why it is 49 not 50

        b, t, n = seq.size()
        device = seq.device

        # forward the GPT model itself
        if noise:
            # add random walk noise to the input
            seq = seq + torch.cumsum(torch.randn_like(seq) * 0.003, dim=1)
        x = self.function_encoder(seq)   # [b t n] -> [b t c]
        x = x + self.position_embedding(x) # add position embedding

        for ln, attn_block, ffn in self.transformer:
            # ln: layer normalization
            # attn_block: self attention layer
            # ffn: feed forward network (a two-layer MLP)
            # ====================================================
            # TODO: implement one forward pass of the transformer (do not modify other part of this class)

            # attention
            attn_out = attn_block(x)
            x = x + attn_out
            x = ln(x)

            # feed-forward
            ffn_out = ffn(x)
            x = x + ffn_out
            x = ln(x)


            # ====================================================

        x = self.function_decoder(x)   # [b t c] -> [b t n]

        return x

    def predict(self, in_seq, predict_steps=30, tstart=0):
        # in_seq will be in shape [batch_size, 10, 100]
        out_seq = torch.zeros(in_seq.size(0), predict_steps, in_seq.size(2)).to(in_seq.device)
        for t in range(predict_steps):
            if self.training:
                shifted_in_seq = self.forward(in_seq, noise=True, tstart=tstart)
            else:
                shifted_in_seq = self.forward(in_seq, noise=False, tstart=tstart)
            in_seq = torch.cat((in_seq, shifted_in_seq[:, -1:]), dim=1)
            out_seq[:, t:t+1] = shifted_in_seq[:, -1:]

        return out_seq
```

Train the model

In [16]:

```
### do not modify this cell!
### ==============================
def train_a_gpt(lr,
                num_layers,
                batch_size,
                num_epochs):
    device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
    print('Using device:', device)
    # train a GPT model with num_layers
    model = PDEGPT(num_layers=num_layers)
    model = model.to(device)

    # build dataloader
    train_set = torch.utils.data.TensorDataset(torch.tensor(train_data, dtype=torch.float32))
    train_loader = torch.utils.data.DataLoader(train_set, batch_size=batch_size, shuffle=True, num_workers=4)

    test_set = torch.utils.data.TensorDataset(torch.tensor(test_data, dtype=torch.float32))
    test_loader = torch.utils.data.DataLoader(test_set, batch_size=8, shuffle=False, num_workers=4)

    optimizer = torch.optim.AdamW(model.parameters(), lr=lr)
    scheduler = torch.optim.lr_scheduler.OneCycleLR(optimizer, max_lr=lr, total_steps=num_epochs*len(train_loader), final_div_factor=1e3)

    train_history = []
    test_history = []
    loss_buffer = []
    for epoch in range(num_epochs):
        model.train()
        for i, seq in enumerate(train_loader):
            seq = seq[0].to(device)
            optimizer.zero_grad()
            # training in block, not always using teacher forcing
            if i % 3 == 0:
                loss = 0
                ct = 0
                for b in range(0, seq.size(1)-20, 10):
                    pred = model.predict(seq[:, b:b+10], predict_steps=10, tstart=b)
                    loss += F.mse_loss(pred, seq[:, b+10:b+20])
                    ct += 1
                loss /= ct
            else:
                pred = model(seq[:, :-1])
                loss = F.mse_loss(pred, seq[:, 1:])
            loss.backward()
            optimizer.step()
            loss_buffer.append(loss.item())

            if i % 20 == 0:
                print("epoch %d, iter %d, loss %.3f" % (epoch, i, np.mean(loss_buffer)))
                loss_buffer = []
        train_history.append(loss.item())
        scheduler.step()

        model.eval()
        test_losses = []
        with torch.no_grad():
            for i, seq in enumerate(test_loader):
                seq = seq[0].to(device)
                pred = model.predict(seq[:, :10])
                loss = F.mse_loss(pred, seq[:, 10:])

                test_losses.append(loss.item())
        print("epoch %d, test loss %.3f" % (epoch, np.mean(test_losses)))
        test_history.append(np.mean(test_losses))

    return model, train_history, test_history


def eval_and_visualize(trained_model):
    device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
    print('Using device:', device)
    test_set = torch.utils.data.TensorDataset(torch.tensor(test_data, dtype=torch.float32))
    test_loader = torch.utils.data.DataLoader(test_set, batch_size=8, shuffle=False, num_workers=4)

    trained_model.eval()
    test_losses = []
    with torch.no_grad():
        for i, seq in enumerate(test_loader):
            seq = seq[0].to(device)
            pred = trained_model.predict(seq[:, :10])
            loss = F.mse_loss(pred, seq[:, 10:])

            test_losses.append(loss.item())

        print('Final evaluation error:', np.mean(test_losses))

        # randomly pick a sample to evaluate and visualize
        seed_everything()
        idx = np.random.randint(0, len(test_data))
        seq = torch.tensor(test_data[idx:idx+1], dtype=torch.float32).to(device)
        pred = trained_model.predict(seq[:, :10])
        pred_seq = torch.cat((seq[:, :10], pred), dim=1).cpu().numpy()[0]

        plt.plot(np.linspace(0, 16, 100), seq.cpu().numpy()[0, -1], label='ground truth')
        plt.scatter(np.linspace(0, 16, 100), pred_seq[-1], label='prediction', c='g')
        plt.legend()
        plt.show()
```

```
    return
```

In [17]:
```
### you can change the hyperparameter of "train_a_gpt" to see how it affects the performance, please do not modify the other parts
### ==============================

torch.cuda.empty_cache()
# change the parameters to see how it affects the performance
model, train_history, test_history = train_a_gpt(lr=1.05e-3, num_layers=10, batch_size=32, num_epochs=150)
eval_and_visualize(model)

plt.plot(train_history, label='train loss')  # simply visualize the training loss
plt.plot(test_history, label='test loss')
plt.legend()
```

```
Using device: cuda:0
Total number of trainable parameters: 3018916
```

```
/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py:561: UserWarning: This DataLoader will create 4 worker processes in total. O
ur suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that exce
ssive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.
  warnings.warn(_create_warning_msg(
```

```
epoch 0, iter 0, loss 0.451
epoch 0, iter 20, loss 0.548
epoch 0, iter 40, loss 0.561
epoch 0, iter 60, loss 0.551
epoch 0, test loss 0.642
epoch 1, iter 0, loss 0.586
epoch 1, iter 20, loss 0.554
epoch 1, iter 40, loss 0.535
epoch 1, iter 60, loss 0.533
epoch 1, test loss 0.617
epoch 2, iter 0, loss 0.574
epoch 2, iter 20, loss 0.517
epoch 2, iter 40, loss 0.500
epoch 2, iter 60, loss 0.512
epoch 2, test loss 0.586
epoch 3, iter 0, loss 0.448
epoch 3, iter 20, loss 0.491
epoch 3, iter 40, loss 0.487
epoch 3, iter 60, loss 0.466
epoch 3, test loss 0.554
epoch 4, iter 0, loss 0.477
epoch 4, iter 20, loss 0.458
epoch 4, iter 40, loss 0.444
epoch 4, iter 60, loss 0.447
epoch 4, test loss 0.515
epoch 5, iter 0, loss 0.391
epoch 5, iter 20, loss 0.428
epoch 5, iter 40, loss 0.409
epoch 5, iter 60, loss 0.397
epoch 5, test loss 0.481
epoch 6, iter 0, loss 0.421
epoch 6, iter 20, loss 0.395
epoch 6, iter 40, loss 0.379
epoch 6, iter 60, loss 0.359
epoch 6, test loss 0.446
epoch 7, iter 0, loss 0.402
epoch 7, iter 20, loss 0.360
epoch 7, iter 40, loss 0.339
epoch 7, iter 60, loss 0.342
epoch 7, test loss 0.409
epoch 8, iter 0, loss 0.332
epoch 8, iter 20, loss 0.325
epoch 8, iter 40, loss 0.322
epoch 8, iter 60, loss 0.299
epoch 8, test loss 0.376
epoch 9, iter 0, loss 0.328
epoch 9, iter 20, loss 0.290
epoch 9, iter 40, loss 0.299
epoch 9, iter 60, loss 0.279
epoch 9, test loss 0.342
epoch 10, iter 0, loss 0.251
epoch 10, iter 20, loss 0.277
epoch 10, iter 40, loss 0.254
epoch 10, iter 60, loss 0.243
epoch 10, test loss 0.310
epoch 11, iter 0, loss 0.262
epoch 11, iter 20, loss 0.235
epoch 11, iter 40, loss 0.227
epoch 11, iter 60, loss 0.232
epoch 11, test loss 0.279
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epoch 12, iter 40, loss 0.210
epoch 12, iter 60, loss 0.196
epoch 12, test loss 0.249
epoch 13, iter 0, loss 0.182
epoch 13, iter 20, loss 0.189
epoch 13, iter 40, loss 0.192
epoch 13, iter 60, loss 0.163
epoch 13, test loss 0.224
epoch 14, iter 0, loss 0.175
epoch 14, iter 20, loss 0.171
epoch 14, iter 40, loss 0.158
epoch 14, iter 60, loss 0.161
epoch 14, test loss 0.202
epoch 15, iter 0, loss 0.153
epoch 15, iter 20, loss 0.148
epoch 15, iter 40, loss 0.141
epoch 15, iter 60, loss 0.134
epoch 15, test loss 0.179
epoch 16, iter 0, loss 0.139
epoch 16, iter 20, loss 0.131
epoch 16, iter 40, loss 0.128
epoch 16, iter 60, loss 0.119
epoch 16, test loss 0.160
epoch 17, iter 0, loss 0.100
epoch 17, iter 20, loss 0.112
epoch 17, iter 40, loss 0.110
epoch 17, iter 60, loss 0.105
epoch 17, test loss 0.143
epoch 18, iter 0, loss 0.103
epoch 18, iter 20, loss 0.105
epoch 18, iter 40, loss 0.092
epoch 18, iter 60, loss 0.091
epoch 18, test loss 0.127
epoch 19, iter 0, loss 0.091
epoch 19, iter 20, loss 0.084
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epoch 19, iter 40, loss 0.088
epoch 19, iter 60, loss 0.080
epoch 19, test loss 0.114
epoch 20, iter 0, loss 0.081
epoch 20, iter 20, loss 0.078
epoch 20, iter 40, loss 0.078
epoch 20, iter 60, loss 0.071
epoch 20, test loss 0.104
epoch 21, iter 0, loss 0.074
epoch 21, iter 20, loss 0.072
epoch 21, iter 40, loss 0.064
epoch 21, iter 60, loss 0.062
epoch 21, test loss 0.093
epoch 22, iter 0, loss 0.072
epoch 22, iter 20, loss 0.058
epoch 22, iter 40, loss 0.063
epoch 22, iter 60, loss 0.061
epoch 22, test loss 0.086
epoch 23, iter 0, loss 0.048
epoch 23, iter 20, loss 0.056
epoch 23, iter 40, loss 0.056
epoch 23, iter 60, loss 0.051
epoch 23, test loss 0.077
epoch 24, iter 0, loss 0.050
epoch 24, iter 20, loss 0.048
epoch 24, iter 40, loss 0.050
epoch 24, iter 60, loss 0.050
epoch 24, test loss 0.072
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epoch 25, iter 40, loss 0.047
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epoch 25, test loss 0.067
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epoch 26, iter 60, loss 0.042
epoch 26, test loss 0.067
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epoch 27, test loss 0.058
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epoch 28, iter 60, loss 0.034
epoch 28, test loss 0.054
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epoch 29, test loss 0.051
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epoch 30, iter 60, loss 0.031
epoch 30, test loss 0.049
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epoch 31, iter 20, loss 0.030
epoch 31, iter 40, loss 0.034
epoch 31, iter 60, loss 0.028
epoch 31, test loss 0.048
epoch 32, iter 0, loss 0.019
epoch 32, iter 20, loss 0.031
epoch 32, iter 40, loss 0.026
epoch 32, iter 60, loss 0.028
epoch 32, test loss 0.045
epoch 33, iter 0, loss 0.027
epoch 33, iter 20, loss 0.025
epoch 33, iter 40, loss 0.026
epoch 33, iter 60, loss 0.027
epoch 33, test loss 0.044
epoch 34, iter 0, loss 0.026
epoch 34, iter 20, loss 0.027
epoch 34, iter 40, loss 0.025
epoch 34, iter 60, loss 0.024
epoch 34, test loss 0.044
epoch 35, iter 0, loss 0.024
epoch 35, iter 20, loss 0.026
epoch 35, iter 40, loss 0.024
epoch 35, iter 60, loss 0.024
epoch 35, test loss 0.043
epoch 36, iter 0, loss 0.019
epoch 36, iter 20, loss 0.025
epoch 36, iter 40, loss 0.021
epoch 36, iter 60, loss 0.024
epoch 36, test loss 0.037
epoch 37, iter 0, loss 0.021
epoch 37, iter 20, loss 0.024
epoch 37, iter 40, loss 0.021
epoch 37, iter 60, loss 0.022
epoch 37, test loss 0.035
epoch 38, iter 0, loss 0.018
epoch 38, iter 20, loss 0.020
epoch 38, iter 40, loss 0.021
epoch 38, iter 60, loss 0.021
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epoch 38, test loss 0.034
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epoch 39, iter 20, loss 0.020
epoch 39, iter 40, loss 0.018
epoch 39, iter 60, loss 0.023
epoch 39, test loss 0.034
epoch 40, iter 0, loss 0.015
epoch 40, iter 20, loss 0.020
epoch 40, iter 40, loss 0.020
epoch 40, iter 60, loss 0.020
epoch 40, test loss 0.033
epoch 41, iter 0, loss 0.017
epoch 41, iter 20, loss 0.022
epoch 41, iter 40, loss 0.019
epoch 41, iter 60, loss 0.017
epoch 41, test loss 0.032
epoch 42, iter 0, loss 0.011
epoch 42, iter 20, loss 0.019
epoch 42, iter 40, loss 0.020
epoch 42, iter 60, loss 0.017
epoch 42, test loss 0.032
epoch 43, iter 0, loss 0.017
epoch 43, iter 20, loss 0.019
epoch 43, iter 40, loss 0.021
epoch 43, iter 60, loss 0.018
epoch 43, test loss 0.031
epoch 44, iter 0, loss 0.023
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epoch 44, iter 40, loss 0.018
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epoch 44, test loss 0.033
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epoch 45, iter 40, loss 0.016
epoch 45, iter 60, loss 0.019
epoch 45, test loss 0.029
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epoch 46, iter 60, loss 0.017
epoch 46, test loss 0.028
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epoch 47, test loss 0.029
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epoch 48, test loss 0.027
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epoch 50, test loss 0.027
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epoch 57, test loss 0.025
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epoch 60, test loss 0.022
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epoch 61, test loss 0.025
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epoch 70, test loss 0.019
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epoch 76, test loss 0.019
epoch 77, iter 0, loss 0.008
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epoch 84, test loss 0.019
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epoch 86, test loss 0.019
epoch 87, iter 0, loss 0.006
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epoch 87, test loss 0.018
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epoch 90, test loss 0.017
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epoch 91, test loss 0.017
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epoch 93, test loss 0.017
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epoch 94, test loss 0.017
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epoch 95, iter 60, loss 0.009
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epoch 96, iter 20, loss 0.009
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epoch 96, test loss 0.017
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epoch 97, iter 40, loss 0.008
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epoch 97, test loss 0.017
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epoch 98, test loss 0.018
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epoch 99, test loss 0.017
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epoch 101, test loss 0.018
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epoch 102, iter 60, loss 0.008
epoch 102, test loss 0.016
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epoch 104, test loss 0.016
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epoch 105, test loss 0.014
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epoch 107, test loss 0.018
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epoch 108, test loss 0.015
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epoch 109, test loss 0.015
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epoch 110, test loss 0.017
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epoch 111, test loss 0.016
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epoch 112, test loss 0.015
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epoch 113, test loss 0.016
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epoch 114, test loss 0.017
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epoch 115, iter 60, loss 0.007
epoch 115, test loss 0.016
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epoch 116, test loss 0.015
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epoch 125, test loss 0.014
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epoch 126, test loss 0.015
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epoch 127, test loss 0.014
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epoch 136, iter 60, loss 0.007
epoch 136, test loss 0.015
epoch 137, iter 0, loss 0.005
epoch 137, iter 20, loss 0.007
epoch 137, iter 40, loss 0.006
epoch 137, iter 60, loss 0.007
epoch 137, test loss 0.014
epoch 138, iter 0, loss 0.005
epoch 138, iter 20, loss 0.007
epoch 138, iter 40, loss 0.006
epoch 138, iter 60, loss 0.006
epoch 138, test loss 0.013
epoch 139, iter 0, loss 0.007
epoch 139, iter 20, loss 0.007
epoch 139, iter 40, loss 0.007
epoch 139, iter 60, loss 0.006
epoch 139, test loss 0.013
epoch 140, iter 0, loss 0.006
epoch 140, iter 20, loss 0.006
epoch 140, iter 40, loss 0.006
epoch 140, iter 60, loss 0.006
epoch 140, test loss 0.014
epoch 141, iter 0, loss 0.006
epoch 141, iter 20, loss 0.007
epoch 141, iter 40, loss 0.007
epoch 141, iter 60, loss 0.005
epoch 141, test loss 0.013
epoch 142, iter 0, loss 0.007
epoch 142, iter 20, loss 0.006
epoch 142, iter 40, loss 0.006
epoch 142, iter 60, loss 0.006
epoch 142, test loss 0.012
epoch 143, iter 0, loss 0.005
epoch 143, iter 20, loss 0.006
epoch 143, iter 40, loss 0.006
epoch 143, iter 60, loss 0.006
epoch 143, test loss 0.014
epoch 144, iter 0, loss 0.006
epoch 144, iter 20, loss 0.006
epoch 144, iter 40, loss 0.006
epoch 144, iter 60, loss 0.006
epoch 144, test loss 0.014
epoch 145, iter 0, loss 0.008
epoch 145, iter 20, loss 0.007
epoch 145, iter 40, loss 0.007
epoch 145, iter 60, loss 0.006
epoch 145, test loss 0.013
epoch 146, iter 0, loss 0.007
epoch 146, iter 20, loss 0.006
epoch 146, iter 40, loss 0.006
epoch 146, iter 60, loss 0.006
epoch 146, test loss 0.013
epoch 147, iter 0, loss 0.004
epoch 147, iter 20, loss 0.006
epoch 147, iter 40, loss 0.005
epoch 147, iter 60, loss 0.006
epoch 147, test loss 0.013
epoch 148, iter 0, loss 0.006
epoch 148, iter 20, loss 0.006
epoch 148, iter 40, loss 0.006
epoch 148, iter 60, loss 0.006
epoch 148, test loss 0.013
epoch 149, iter 0, loss 0.005
epoch 149, iter 20, loss 0.007
epoch 149, iter 40, loss 0.006
epoch 149, iter 60, loss 0.006
epoch 149, test loss 0.013
Using device: cuda:0
Final evaluation error: 0.0127186065656133
```
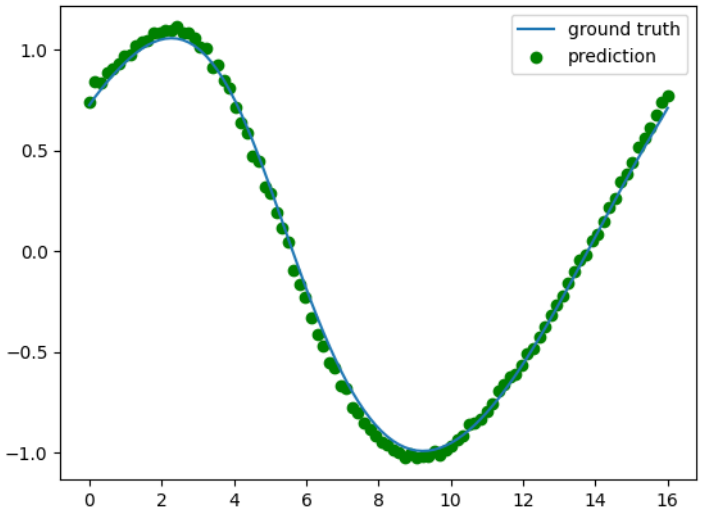
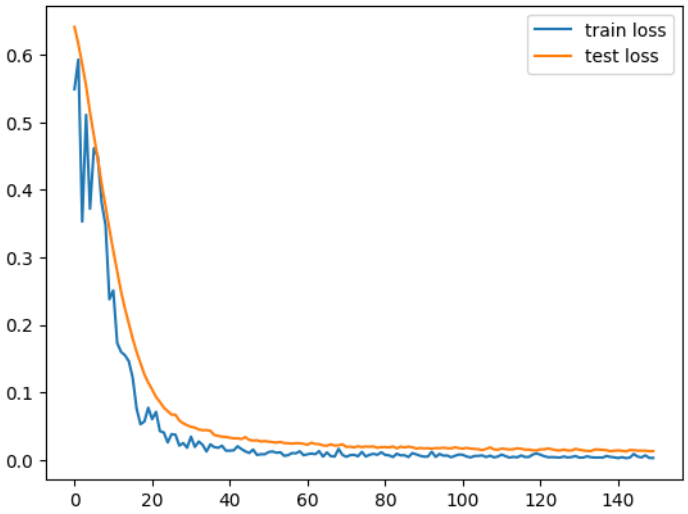



Out[17]: <matplotlib.legend.Legend at 0x7f242630c640>



In [17]: