Homework 02-2: due 2022/03/31 23:59 (70%)

- Tutorial : [https://machinelearningmastery.com/pytorch-tutorial-develop-deep-learning-models/ (https://machinelearningmastery.com/pytorch-tutorial-develop-deep-learning-models/)](https://machinelearningmastery.com/pytorch-tutorial-develop-deep-learning-models/)

- After you go through the tutorials, you should be able to work on this assignment.

- Please answer the following questions and work directly on this jupyter notebook.

- Make sure the code can be run and show the result and figures properly.

- Please write down your observation with markdown in this notebook briefly.

You will train a regression model in this part. The data is Concrete Compressive Strength Dataset, you can find the details of each column at [https://archive.ics.uci.edu/ml/datasets/concrete+compressive+strength (https://archive.ics.uci.edu/ml/datasets/concrete+compressive+strength)](https://archive.ics.uci.edu/ml/datasets/concrete+compressive+strength). In this part, please predict the strength of concrete.

In [1]:

```
# Import necessary modules
%matplotlib inline
import pandas as pd
import numpy as np
import random
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader, random_split
import matplotlib.pyplot as plt
from tqdm.notebook import tqdm
from sklearn.preprocessing import MinMaxScaler
```

In [2]:

```
# For reproduce the result
torch.manual_seed(0)
random.seed(0)
np.random.seed(0)
```

1. Define the model and dataset (10%)

1.1 Please follow the tutorial to create a class *ConcreteDataset*, for loading the data you need and also do the *Min-Max scaling* to the *feature and label*. (5%)

In [3]:

```
class ConcreteDataset(Dataset):
    def __init__(self, csv_path):
        df = pd.read_csv(csv_path)
        self.X = df.iloc[:, :-1].values
        self.y = df.iloc[:, -1].values
        self.X_scaler = MinMaxScaler()
        self.y_scaler = MinMaxScaler()
        self.X = self.X_scaler.fit_transform(self.X)
        self.y = self.y.reshape(len(self.y), 1)
        self.y = self.y_scaler.fit_transform(self.y)


    def __len__(self):
        return len(self.X)

    def __getitem__(self, idx):
        feature = torch.tensor(self.X[idx], dtype=torch.float32)
        label = torch.tensor(self.y[idx], dtype=torch.float32)
        return feature, label
```

1.2 By following the tutorial, try to create a class *MLP(Neural Network)* with *three hidden layers* as your network architecture. Also, for the convenience of implementation, please set the numbers of hidden nodes and the activation functions as input variables to the foward functions.(5%)

In [4]:

```
class MLP(nn.Module):
    def __init__(self, input_ch=30, first_layers=256, second_layers=64, third_layers=8,
activation=nn.Sigmoid(), output_act=nn.Tanh()):
        super(MLP, self).__init__()
        self.model = nn.Sequential( nn.Linear(input_ch, first_layers),
                                    activation,
                                    nn.Linear(first_layers, second_layers),
                                    activation,
                                    nn.Linear(second_layers, third_layers),
                                    activation,
                                    nn.Linear(third_layers, 1) )



        self.output_act = output_act

    def forward(self, X):
        X = self.model(X)
        X = self.output_act(X)
        return X
```

2. Train the model (60%)

2.1 Please load the *train.csv/ validation.csv* in ./data, and turn them into dataloader with batch size 64 and determine whether shuffle or not. (5%)

In [5]:

```
train_ds = ConcreteDataset("./data/train.csv")
val_ds = ConcreteDataset("./data/validation.csv")
```

In [6]:

```
train_dl = DataLoader(train_ds, batch_size=64, shuffle=True)
val_dl = DataLoader(val_ds, batch_size=64, shuffle=False)
```

2.2 Create two MLP model from the table below and *print the model* (10%):

	Hidden Layer 1	Hidden Layer 2	Hidden Layer 3	Activation in each hidden nodes	Activation for output
Model1	256	64	8	Tanh	Tanh
Model2	64	16	8	Sigmoid	Identity

In [7]:

```
models = {"Model1" : MLP(input_ch=8, first_layers=256, second_layers=64, third_layers=8
, activation=nn.Tanh(), output_act = nn.Tanh()),
            "Model2" : MLP(input_ch=8, first_layers=64, second_layers=16, third_layers=
8, activation=nn.Tanh(), output_act = nn.Identity())}
```

In [8]:

```
for name, model in models.items():
    print(model)
```

```
MLP(
  (model): Sequential(
    (0): Linear(in_features=8, out_features=256, bias=True)
    (1): Tanh()
    (2): Linear(in_features=256, out_features=64, bias=True)
    (3): Tanh()
    (4): Linear(in_features=64, out_features=8, bias=True)
    (5): Tanh()
    (6): Linear(in_features=8, out_features=1, bias=True)
  )
  (output_act): Tanh()
)
MLP(
  (model): Sequential(
    (0): Linear(in_features=8, out_features=64, bias=True)
    (1): Tanh()
    (2): Linear(in_features=64, out_features=16, bias=True)
    (3): Tanh()
    (4): Linear(in_features=16, out_features=8, bias=True)
    (5): Tanh()
    (6): Linear(in_features=8, out_features=1, bias=True)
  )
  (output_act): Identity()
)
```

2.3 Train the above two models with the same hyperpameters below and do the validation in every epoch. Choose the appropriate type of loss function according to the task. (25%)

(Note. You should record the training/validation loss every epoch)

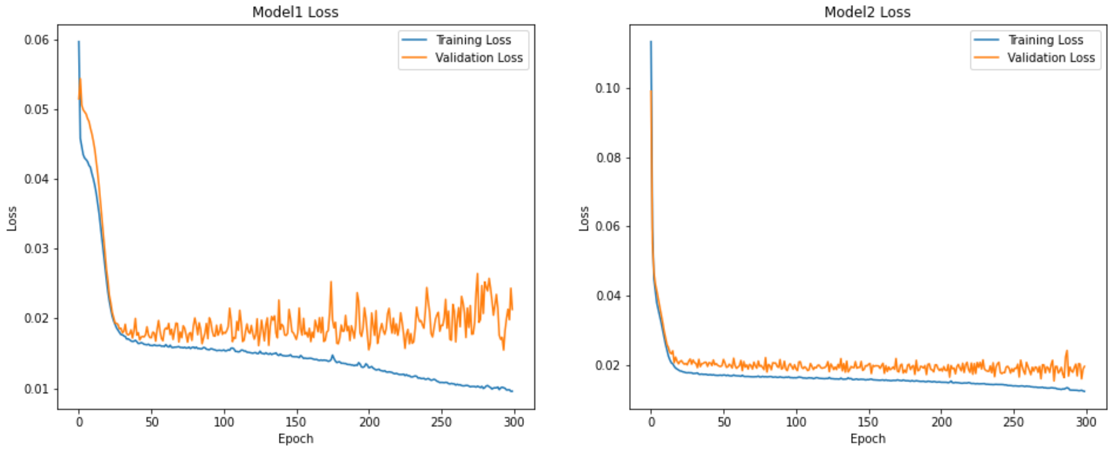
	Learning rate	epochs	optimizer	momentum
Hyperparameter	0.01	300	SGD	0.9

In [9]:

```
learning_rate = 0.01
criterion = nn.MSELoss()
max_epoch = 300
result = {}

for name, model in models.items():
    optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=0.9)
    pbar = tqdm(range(max_epoch))
    result[name] = {"Training Loss":[], "Validation Loss":[]}
    for i in pbar:
        training_loss = 0
        val_loss = 0
        for inputs, label in train_dl:
            optimizer.zero_grad()
            pred = model(inputs)
            loss = criterion(pred, label)
            loss.backward()
            optimizer.step()
            training_loss+=loss.detach().numpy()

        for inputs, label in val_dl:
            with torch.no_grad():
                pred = model(inputs)
                loss = criterion(pred, label)
                val_loss+=loss.numpy()
        result[name]["Training Loss"].append(training_loss/len(train_dl))
        result[name]["Validation Loss"].append(val_loss/len(val_dl))
```

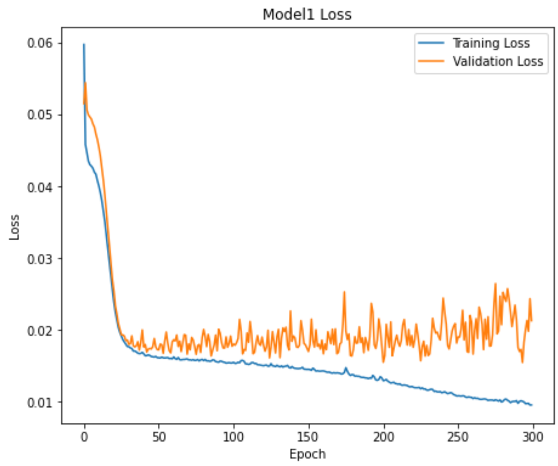
2.4 Please include the plot that shows how the training/validation loss vary with the training epoch. Show the plots using the above two models and write down the observation. (5%)

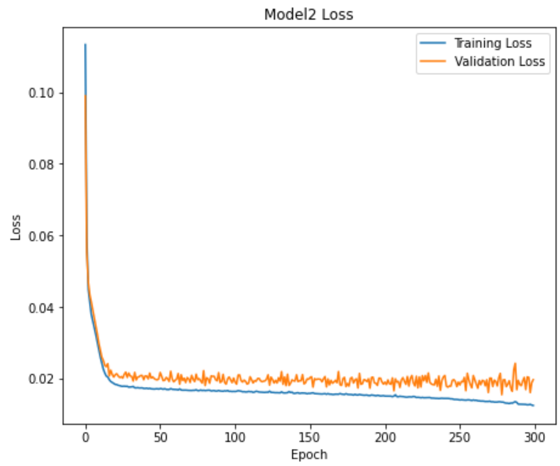
Here is the example figure



In [10]:

```
fig, ax = plt.subplots(1, 2, figsize=(16, 6))
fig.subplots_adjust(wspace=0.2)
for i, (name, model) in enumerate(models.items()):
    ax[i].set_title(f"{name} Loss")
    ax[i].set_xlabel("Epoch")
    ax[i].set_ylabel("Loss")
    ax[i].plot(range(len(result[name][f"Training Loss"])), result[name][f"Training Los
s"], label=f"Training Loss")
    ax[i].plot(range(len(result[name][f"Validation Loss"])),  result[name][f"Validation
Loss"], label=f"Validation Loss")
    ax[i].legend()
plt.show()
```





2.5 From the observation of the previous question, please determine an appropriate epoch and retrain the two models to avoid overfitting. Also, draw the loss plot of two models and save the last model as *model1.pth* and *model2.pth*. (10%)

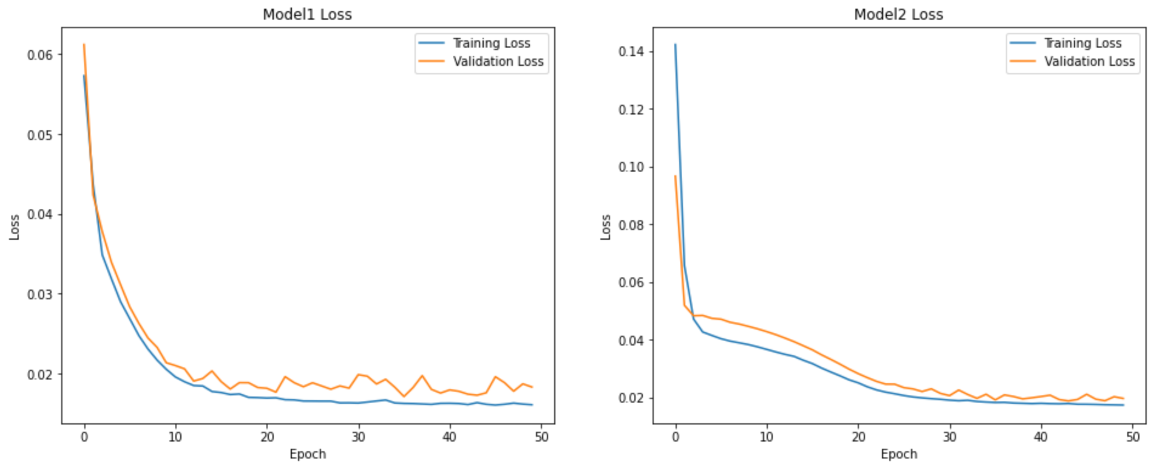
(Note. You should reload the models and the optimizer, otherwise, you will resume from the previous stop.)

In [83]:

```
models = {"Model1" : MLP(input_ch=8, first_layers=256, second_layers=64, third_layers=8
, activation=nn.Tanh(), output_act = nn.Tanh()),
            "Model2" : MLP(input_ch=8, first_layers=64, second_layers=16, third_layers=
8, activation=nn.Tanh(), output_act = nn.Identity())}
learning_rate = 0.01
criterion = nn.MSELoss()
max_epoch = 50
result = {}

for name, model in models.items():
    optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=0.9)
    pbar = tqdm(range(max_epoch))
    result[name] = {"Training Loss":[], "Validation Loss":[]}
    for i in pbar:
        training_loss = 0
        val_loss = 0
        for inputs, label in train_dl:
            optimizer.zero_grad()
            pred = model(inputs)
            loss = criterion(pred, label)
            loss.backward()
            optimizer.step()
            training_loss+=loss.detach().numpy()

        for inputs, label in val_dl:
            with torch.no_grad():
                pred = model(inputs)
                loss = criterion(pred, label)
                val_loss+=loss.numpy()
        result[name]["Training Loss"].append(training_loss/len(train_dl))
        result[name]["Validation Loss"].append(val_loss/len(val_dl))

    torch.save(model.state_dict(), f"{name}.pth")
```

In [84]:

```
fig, ax = plt.subplots(1, 2, figsize=(16, 6))
fig.subplots_adjust(wspace=0.2)
for i, (name, model) in enumerate(models.items()):
    ax[i].set_title(f"{name} Loss")
    ax[i].set_xlabel("Epoch")
    ax[i].set_ylabel("Loss")
    ax[i].plot(range(len(result[name][f"Training Loss"])), result[name][f"Training Los
s"], label=f"Training Loss")
    ax[i].plot(range(len(result[name][f"Validation Loss"])),  result[name][f"Validation
Loss"], label=f"Validation Loss")
    ax[i].legend()
plt.show()
```



2.6 Please load the checkpoints saved from previous question and calculate the mean squared error on test dataset for two models respectively. Also, make a dataframe with target and prediction like below and save it as *regression.csv* (5%)

Target	Model1	Model2
24.05	26.35	27.04
21.67	32.78	21.95

In [85]:

```
from sklearn.metrics import mean_squared_error
models = {"Model1" : MLP(input_ch=8, first_layers=256, second_layers=64, third_layers=8
, activation=nn.Tanh(), output_act = nn.Tanh()),
            "Model2" : MLP(input_ch=8, first_layers=64, second_layers=16, third_layers=
8, activation=nn.Tanh(), output_act = nn.Identity())}
test_ds = ConcreteDataset("./data/test.csv")
test_dl = DataLoader(test_ds, batch_size=len(test_ds), shuffle=False)
output = {}
for name, model in models.items():
    for X, y in test_dl:
        model.load_state_dict(torch.load(f"{name}.pth"))
        model.eval()
        with torch.no_grad():
            pred = model(X)
            output["Target"] = test_ds.y_scaler.inverse_transform(y).squeeze()
            output[name] = test_ds.y_scaler.inverse_transform(pred).squeeze()
        print(f"Mean Squared Error ({name}): ", mean_squared_error(output["Target"], ou
tput[name]))
```

```
Mean Squared Error (Model1):  123.53380721961621
Mean Squared Error (Model2):  125.56298670792383
```

In [86]:

```
out = pd.DataFrame(output)
```

In [87]:

```
out.to_csv("regression.csv")
```