Import libraries and the dataset

In [1]:
```
# Import libraries
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from torch.nn.functional import normalize
from torchvision import transforms
from sklearn.preprocessing import MinMaxScaler
#from sklearn.preprocessing import StandardScaler
from torch.utils.data import DataLoader
from torch.autograd.grad_mode import no_grad
from sklearn.metrics import mean_squared_error
import matplotlib.dates as mdates
import random

# Device configuration
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
device
```

Out[1]:
```
device(type='cuda', index=0)
```

In [2]:
```
# Set all random factors to be deterministic
def deterministic(seed):
  torch.manual_seed(seed)
  np.random.seed(seed)
  random.seed(seed)
  torch.cuda.manual_seed(seed)
  torch.cuda.manual_seed_all(seed)
  torch.backends.cudnn.deterministic = True
  torch.backends.cudnn.benchmark = False
```

In [3]:
```
# Load dataset
dataset = pd.read_csv("QQQ.csv")
```

In [4]:
```
print(f"dataset shape: {dataset.shape}")
```

```
dataset shape: (5952, 7)
```

In [5]:
```
dataset.head()
```

Out[5]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	1999-03-11	51.43750	51.734375	50.31250	51.3125	44.226849	9688600
1	1999-03-12	51.12500	51.156250	49.65625	50.0625	43.149475	8743600
2	1999-03-15	50.43750	51.562500	49.90625	51.5000	44.388466	6369000
3	1999-03-16	51.71875	52.156250	51.15625	51.9375	44.765564	4905800
4	1999-03-17	51.93750	52.000000	51.40625	51.5625	44.442318	3965000

Data Processing

In [6]:
```
# Add a label to the dataset
df_label = np.append(np.array(dataset["Close"][1:]), np.nan)
dataset["Label"] = df_label
dataset
```

Out[6]:

	Date	Open	High	Low	Close	Adj Close	Volume	
0	1999-03-11	51.437500	51.734375	50.312500	51.312500	44.226849	9688600	50
1	1999-03-12	51.125000	51.156250	49.656250	50.062500	43.149475	8743600	51
2	1999-03-15	50.437500	51.562500	49.906250	51.500000	44.388466	6369000	51
3	1999-03-16	51.718750	52.156250	51.156250	51.937500	44.765564	4905800	51
4	1999-03-17	51.937500	52.000000	51.406250	51.562500	44.442318	3965000	52
...	...	...	...	...	...	...	...	
5947	2022-10-26	278.459991	283.980011	277.429993	277.929993	277.929993	63492400	272
5948	2022-10-27	276.790009	278.279999	272.339996	272.869995	272.869995	57760300	28
5949	2022-10-28	272.230011	281.700012	272.059998	281.220001	281.220001	62651300	27
5950	2022-10-31	278.920013	279.760010	275.989990	277.950012	277.950012	47742000	275
5951	2022-11-01	281.500000	282.070007	274.739990	275.109985	275.109985	45791000	

5952 rows × 8 columns

In [7]:
```
# A function to create a baseline model
def baseline_prediction(dataframe, look_back):
  baseline = []
  df_close = np.array(dataframe["Close"])
  for i in range(len(dataframe)):
    if i < look_back:
      baseline.append(np.nan)
    else:
      value = 0
      for j in range(look_back):
        value += df_close[i-j] - df_close[i-j-1]
      value = df_close[i] + value/look_back
      baseline.append(value)
  return baseline
```

In [8]:
```
# Create a baseline model with a lookback period of 64
baseline = baseline_prediction(dataset, 64)
dataset["Baseline"] = baseline
dataset
```

Out[8]:

	Date	Open	High	Low	Close	Adj Close	Volume	
0	1999-03-11	51.437500	51.734375	50.312500	51.312500	44.226849	9688600	50
1	1999-03-12	51.125000	51.156250	49.656250	50.062500	43.149475	8743600	51
2	1999-03-15	50.437500	51.562500	49.906250	51.500000	44.388466	6369000	51
3	1999-03-16	51.718750	52.156250	51.156250	51.937500	44.765564	4905800	51
4	1999-03-17	51.937500	52.000000	51.406250	51.562500	44.442318	3965000	52
...	...	...	...	...	...	...	...	
5947	2022-10-26	278.459991	283.980011	277.429993	277.929993	277.929993	63492400	272
5948	2022-10-27	276.790009	278.279999	272.339996	272.869995	272.869995	57760300	28
5949	2022-10-28	272.230011	281.700012	272.059998	281.220001	281.220001	62651300	27
5950	2022-10-31	278.920013	279.760010	275.989990	277.950012	277.950012	47742000	275
5951	2022-11-01	281.500000	282.070007	274.739990	275.109985	275.109985	45791000	

5952 rows × 9 columns

In [9]:

```
# Split the dataset into a training, validation and testing set in a ratio c
training_df = dataset.iloc[:4800, :]
validation_df = dataset.iloc[4800:5375, :]
testing_df = dataset.iloc[5375:, :]
```

In [10]:

```
print(f"Training datafram shape: {training_df.shape}")
print(f"Validation datafram shape: {validation_df.shape}")
print(f"Testing dataframe shape: {testing_df.shape}")
```

```
Training datafram shape: (4800, 9)
Validation datafram shape: (575, 9)
Testing dataframe shape: (577, 9)
```

In [11]:

```
# Create custom dataset to the datasets work in batches
class custom_dataset:
  def __init__(self, dataset, seq_len):
    self._dataset = dataset
    self._seq_len = seq_len
    self._scalar = None
    self._close = None
    self._close_normalized = self.normalized()
    self._feature = self.feature_vector()
    self._label = self.label_vector()
    self._dataset_shape = dataset.shape

  # Normalize the dataset
  def normalized(self):
    self._close = self._dataset.loc[:,"Close"].to_numpy()
    self._scalar = MinMaxScaler()
```

```
    self._close_normalized = self._scalar.fit_transform(self._close.reshape(
    self._close_normalized = self._close_normalized.ravel()
    return self._close_normalized

  # Create feature vectors for the dataset(a lookback period of the close pr
  def feature_vector(self):
    self._feature = []
    for value in range(self._seq_len, len(self._close_normalized)):
      self._feature.append(self._close_normalized[(value-self._seq_len):valu
    self._feature = torch.Tensor(self._feature).unsqueeze(2)
    return self._feature

  # Create labels for the dataset(close price of tomorrow)
  def label_vector(self):
    self._label = torch.Tensor(self._close_normalized[self._seq_len:].reshap
    return self._label

  # inverse transform the normalized data to original scale
  def inverse_transform(self, pred):
    pred = np.array(pred).reshape(-1,1)
    return self._scalar.inverse_transform(pred).ravel()

  # length of the dataset
  def __len__(self):
    return self._label.shape[0]

  # return (feature vector, label)
  def __getitem__(self, index):
    data = self._feature[index]
    label = self._label[index]
    return (data, label)
```

In [12]:

```
# A test to see the custom dataset is working
sequence_length = 10
training_set = custom_dataset(dataset=training_df, seq_len=sequence_length)
validation_set = custom_dataset(dataset=validation_df, seq_len=sequence_leng
testing_set = custom_dataset(dataset=testing_df, seq_len=sequence_length)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:23: UserWarnin
g: Creating a tensor from a list of numpy.ndarrays is extremely slow. Please
consider converting the list to a single numpy.ndarray with numpy.array() be
fore converting to a tensor. (Triggered internally at  ../torch/csrc/utils/t
ensor_new.cpp:201.)
```

In [13]:

```
print(f"Training set feature shape: {training_set._feature.size()}")
print(f"Training set label shape: {training_set._label.size()}")
print(f"Validation set feature shape: {validation_set._feature.size()}")
print(f"Validation set label shape: {validation_set._label.size()}")
print(f"Testing set feature shape: {testing_set._feature.size()}")
print(f"Testing set label shape: {testing_set._label.size()}")
```

```
Training set feature shape: torch.Size([4790, 10, 1])
Training set label shape: torch.Size([4790, 1])
Validation set feature shape: torch.Size([565, 10, 1])
Validation set label shape: torch.Size([565, 1])
Testing set feature shape: torch.Size([567, 10, 1])
Testing set label shape: torch.Size([567, 1])
```

In [14]:

```
# Showing the custom dataset return correct feature vectors and labels
print(f"feature: {training_set._feature[-2]}, label: {training_set._label[-2
print(f"feature: {training_set._feature[-1]}, label: {training_set._label[-1
```

```
feature: tensor([[0.9535],
        [0.9268],
        [0.8989],
        [0.9372],
        [0.9026],
        [0.8907],
        [0.9094],
        [0.8794],
        [0.8908],
        [0.9069]]), label: tensor([0.9128])
feature: tensor([[0.9268],
        [0.8989],
        [0.9372],
        [0.9026],
        [0.8907],
        [0.9094],
        [0.8794],
        [0.8908],
        [0.9069],
        [0.9128]]), label: tensor([0.8867])
```

In [15]:

```
# A test of putting custom datasets into data loaders
batch_size = 32
train_loader = DataLoader(dataset=training_set, batch_size=batch_size)
valid_loader = DataLoader(dataset=validation_set, batch_size=batch_size)
test_loader = DataLoader(dataset=testing_set, batch_size=batch_size)
```

Model Building

In [16]:

```
# RNN
class RNN(nn.Module):
  def __init__(self, input_dim, hidden_dim, layer_dim, seq_len):
    super(RNN, self).__init__()
    self._input_dim = input_dim
    self._hidden_dim = hidden_dim
    self._layer_dim = layer_dim
    self._out = None
    self._h_c = None
    # RNN cell layer
    self._layer_1 = nn.RNN(input_size=self._input_dim, hidden_size=self._hid
    # Fully connected layer
    self.fc = nn.Linear(in_features=self._hidden_dim, out_features=1)

  def forward(self, x):
    # Initial hidden state
    hidden_state = torch.zeros(self._layer_dim, x.size(0), self._hidden_dim)

    self._out, self._h = self._layer_1(x, hidden_state.detach())
    self._out = self._out[:,-1,:].reshape(self._out.size(0), -1)
    self._out = self.fc(self._out)
    return self._out
```

In [17]:

```
# LSTM
class LSTM(nn.Module):
  def __init__(self, input_dim, hidden_dim, layer_dim, seq_len):
    super(LSTM, self).__init__()
    self._input_dim = input_dim
    self._hidden_dim = hidden_dim
    self._layer_dim = layer_dim
    self._out = None
```

```
    self._h_c = None
    # LSTM cell layer
    self._layer_1 = nn.LSTM(input_size=self._input_dim, hidden_size=self._hi
    # Fully connected layer
    self.fc = nn.Linear(in_features=self._hidden_dim, out_features=1)

  def forward(self, x):
    # Initial hidden state and cell state
    hidden_state = torch.zeros(self._layer_dim, x.size(0), self._hidden_dim)
    cell_state = torch.zeros(self._layer_dim, x.size(0), self._hidden_dim).t

    self._out, self._h = self._layer_1(x, (hidden_state.detach(), cell_state
    self._out = self._out[:,-1,:].reshape(self._out.size(0), -1)
    self._out = self.fc(self._out)
    return self._out
```

In [18]:

```
# GRU
class GRU(nn.Module):
  def __init__(self, input_dim, hidden_dim, layer_dim, seq_len):
    super(GRU, self).__init__()
    self._input_dim = input_dim
    self._hidden_dim = hidden_dim
    self._layer_dim = layer_dim
    self._out = None
    self._h = None
    # GRU cell layer
    self._layer_1 = nn.RNN(input_size=self._input_dim, hidden_size=self._hid
    # Fully connected layer
    self.fc = nn.Linear(in_features=self._hidden_dim, out_features=1)

  def forward(self, x):
    # Initial hidden state
    hidden_state = torch.zeros(self._layer_dim, x.size(0), self._hidden_dim)

    self._out, self._h = self._layer_1(x, hidden_state.detach())
    self._out = self._out[:,-1,:].reshape(self._out.size(0), -1)
    self._out = self.fc(self._out)
    return self._out
```

In [19]:

```
# Plot learning curve
def learning_curve(train_loss_list, valid_loss_list):
  fig, ax = plt.subplots(1,2,figsize=[12,8])
  ax[0].plot([i for i in range(len(train_loss_list))], train_loss_list)
  ax[1].plot([i for i in range(len(valid_loss_list))], valid_loss_list, c="c
  ax[0].set_title("Training Loss")
  ax[0].set_xlabel("Epoch")
  ax[0].set_ylabel("Loss")
  ax[1].set_title("Validation Loss")
  ax[1].set_xlabel("Epoch")
  ax[1].set_ylabel("Loss")
  return fig
```

In [21]:

```
# Training of the model
def train(model, train_data, valid_data, max_epochs, early_stopping=5, min_i
  # Parameter
  epoch = 1
  train_loss_list = []
  valid_loss_list = []
  n_no_improvement = 0
  min_loss = np.inf
  while epoch <= max_epochs and n_no_improvement < early_stopping:
    # Training with the training set
```

```
    model.train()
    for (data, label) in train_data:
      data = data.to(device=device, dtype=torch.float32)
      label = label.to(device=device, dtype=torch.float32)

      outputs = model(data)

      loss = criterion(outputs, label)
      optimizer.zero_grad()
      loss.backward()
      optimizer.step()

    # Evaluate with the training set
    with torch.no_grad():
      model.eval()
      loss = 0
      for (data, label) in train_data:
        data = data.to(device=device, dtype=torch.float32)
        label = label.cpu().detach().numpy()
        outputs = model(data).cpu().detach().numpy()
        loss += mean_squared_error(outputs, label)
      train_loss_list.append(loss.item())

    # Evaluate with the validation set
    with torch.no_grad():
      model.eval()
      loss = 0
      for (data, label) in valid_data:
        data = data.to(device=device, dtype=torch.float32)
        label = label.cpu().detach().numpy()
        outputs = model(data).cpu().detach().numpy()
        loss += mean_squared_error(outputs, label)
      valid_loss_list.append(loss.item())
      # Print training epochs' details
      if verbose == True:
        print(f"epoch:{epoch} loss:{loss}")

      # Early stopping
      if min_loss-loss.item() > min_improvement:
        min_loss = loss.item()
        n_no_improvement = 0
      else:
        n_no_improvement += 1

    epoch += 1
  print(f"final loss: {valid_loss_list[-1]}, number of epoch: {epoch-1}")

  # Print a learning curve
  if lr_curve == True:
    fig = learning_curve(train_loss_list, valid_loss_list)
    return model, fig
  else:
    return model, valid_loss_list
```

In [22]:
```
# A function for evaluation
def evaluate(model, test_data):
  model.eval()
  loss = 0
  prediction = []
  with torch.no_grad():
    for (data, label) in test_data:
      data = data.to(device=device, dtype=torch.float32)
      label = label.to(device=device, dtype=torch.float32)
      outputs = model(data)
```

```
      loss += torch.square(outputs-label).sum()
      for value in outputs:
        prediction.append(value.item())
  return outputs, prediction
```

Grid Search of the Optimal Setting

In [23]:

```
# Grid search for the optimal setting in types of the model, sequence length
deterministic(seed=0)

summary = []
for model_type in ["rnn", "lstm", "gru"]:
  for sequence in [2, 16, 64]:
    for hidden_size in [2, 32, 128]:
      for layer_num in [1, 2, 3]:
        # Set sequence
        seq_len = sequence
        # Create respective datasets
        training_set = custom_dataset(dataset=training_df, seq_len=seq_len)
        validation_set = custom_dataset(dataset=validation_df, seq_len=seq_l
        testing_set = custom_dataset(dataset=testing_df, seq_len=seq_len)
        # Create respective dataloaders
        batch_size = 256
        train_loader = DataLoader(dataset=training_set, batch_size=batch_siz
        valid_loader = DataLoader(dataset=validation_set, batch_size=batch_s
        test_loader = DataLoader(dataset=testing_set, batch_size=batch_size)

        input_dim = 1
        # Set hidden sizes
        hidden_dim = hidden_size
        # Set layers
        layer_dim = layer_num
        # Create the model
        if model_type == "rnn":
          model = RNN(input_dim=input_dim, hidden_dim=hidden_dim, layer_dim=
        elif model_type == "lstm":
          model = LSTM(input_dim=input_dim, hidden_dim=hidden_dim, layer_dim
        elif model_type == "gru":
          model = GRU(input_dim=input_dim, hidden_dim=hidden_dim, layer_dim=
        criterion = nn.MSELoss()
        learning_rate = 0.05
        optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
        print(f"model:{model_type} sequence length: {sequence} layer_dim: {l
        model, valid_loss = train(model=model, train_data=train_loader, vali
                                  verbose=False, lr_curve=False)
        summary.append([model_type, sequence, hidden_size, layer_num, len(va
        print("\n")
```

```
model:rnn sequence length: 2 layer_dim: 1 hidden size: 2
final loss: 0.002001175715122372, number of epoch: 73


model:rnn sequence length: 2 layer_dim: 2 hidden size: 2
final loss: 0.17580739129334688, number of epoch: 44


model:rnn sequence length: 2 layer_dim: 3 hidden size: 2
final loss: 0.1860686708241701, number of epoch: 11


model:rnn sequence length: 2 layer_dim: 1 hidden size: 32
final loss: 0.0019961764046456665, number of epoch: 63


model:rnn sequence length: 2 layer_dim: 2 hidden size: 32
final loss: 0.0021124413469806314, number of epoch: 100


model:rnn sequence length: 2 layer_dim: 3 hidden size: 32
final loss: 0.002099802019074559, number of epoch: 100


model:rnn sequence length: 2 layer_dim: 1 hidden size: 128
final loss: 0.0019989247084595263, number of epoch: 59


model:rnn sequence length: 2 layer_dim: 2 hidden size: 128
final loss: 0.0020781329658348113, number of epoch: 70


model:rnn sequence length: 2 layer_dim: 3 hidden size: 128
final loss: 0.0021123046753928065, number of epoch: 100


model:rnn sequence length: 16 layer_dim: 1 hidden size: 2
final loss: 0.0021080808655824512, number of epoch: 44


model:rnn sequence length: 16 layer_dim: 2 hidden size: 2
final loss: 0.002047898538876325, number of epoch: 100


model:rnn sequence length: 16 layer_dim: 3 hidden size: 2
final loss: 0.19241845235228539, number of epoch: 66


model:rnn sequence length: 16 layer_dim: 1 hidden size: 32
final loss: 0.0023625578032806516, number of epoch: 83


model:rnn sequence length: 16 layer_dim: 2 hidden size: 32
final loss: 0.0027754650509450585, number of epoch: 44


model:rnn sequence length: 16 layer_dim: 3 hidden size: 32
final loss: 0.00390842545311898, number of epoch: 62


model:rnn sequence length: 16 layer_dim: 1 hidden size: 128
final loss: 0.0024470856587868184, number of epoch: 42
```

```
model:rnn sequence length: 16 layer_dim: 2 hidden size: 128
final loss: 0.002933638170361519, number of epoch: 49


model:rnn sequence length: 16 layer_dim: 3 hidden size: 128
final loss: 0.0031043102499097586, number of epoch: 68


model:rnn sequence length: 64 layer_dim: 1 hidden size: 2
final loss: 0.0019887804810423404, number of epoch: 98


model:rnn sequence length: 64 layer_dim: 2 hidden size: 2
final loss: 0.07401514425873756, number of epoch: 12


model:rnn sequence length: 64 layer_dim: 3 hidden size: 2
final loss: 0.07401514425873756, number of epoch: 12


model:rnn sequence length: 64 layer_dim: 1 hidden size: 32
final loss: 0.001932700863108039, number of epoch: 77


model:rnn sequence length: 64 layer_dim: 2 hidden size: 32
final loss: 0.0022214577766135335, number of epoch: 79


model:rnn sequence length: 64 layer_dim: 3 hidden size: 32
final loss: 0.002822198672220111, number of epoch: 81


model:rnn sequence length: 64 layer_dim: 1 hidden size: 128
final loss: 0.001657628279644996, number of epoch: 100


model:rnn sequence length: 64 layer_dim: 2 hidden size: 128
final loss: 0.001803642080631107, number of epoch: 100


model:rnn sequence length: 64 layer_dim: 3 hidden size: 128
final loss: 0.17186057940125465, number of epoch: 18


model:lstm sequence length: 2 layer_dim: 1 hidden size: 2
final loss: 0.0026681419112719595, number of epoch: 100


model:lstm sequence length: 2 layer_dim: 2 hidden size: 2
final loss: 0.1876684371381998, number of epoch: 11


model:lstm sequence length: 2 layer_dim: 3 hidden size: 2
final loss: 0.1889768186956644, number of epoch: 16


model:lstm sequence length: 2 layer_dim: 1 hidden size: 32
final loss: 0.0021700514189433306, number of epoch: 100


model:lstm sequence length: 2 layer_dim: 2 hidden size: 32
final loss: 0.13863092847168446, number of epoch: 100
```

```
model:lstm sequence length: 2 layer_dim: 3 hidden size: 32
final loss: 0.18401344865560532, number of epoch: 14


model:lstm sequence length: 2 layer_dim: 1 hidden size: 128
final loss: 0.0020938351517543197, number of epoch: 100


model:lstm sequence length: 2 layer_dim: 2 hidden size: 128
final loss: 0.13187157176434994, number of epoch: 100


model:lstm sequence length: 2 layer_dim: 3 hidden size: 128
final loss: 0.1828029965981841, number of epoch: 14


model:lstm sequence length: 16 layer_dim: 1 hidden size: 2
final loss: 0.003355017921421677, number of epoch: 100


model:lstm sequence length: 16 layer_dim: 2 hidden size: 2
final loss: 0.20948818884789944, number of epoch: 11


model:lstm sequence length: 16 layer_dim: 3 hidden size: 2
final loss: 0.21169697307050228, number of epoch: 11


model:lstm sequence length: 16 layer_dim: 1 hidden size: 32
final loss: 0.003107645083218813, number of epoch: 100


model:lstm sequence length: 16 layer_dim: 2 hidden size: 32
final loss: 0.005369110323954374, number of epoch: 100


model:lstm sequence length: 16 layer_dim: 3 hidden size: 32
final loss: 0.04000360146164894, number of epoch: 100


model:lstm sequence length: 16 layer_dim: 1 hidden size: 128
final loss: 0.0030734005849808455, number of epoch: 100


model:lstm sequence length: 16 layer_dim: 2 hidden size: 128
final loss: 0.005053678760305047, number of epoch: 100


model:lstm sequence length: 16 layer_dim: 3 hidden size: 128
final loss: 0.19698931090533733, number of epoch: 13


model:lstm sequence length: 64 layer_dim: 1 hidden size: 2
final loss: 0.0295064402744174, number of epoch: 100


model:lstm sequence length: 64 layer_dim: 2 hidden size: 2
final loss: 0.07361635193228722, number of epoch: 11


model:lstm sequence length: 64 layer_dim: 3 hidden size: 2
final loss: 0.07471587508916855, number of epoch: 12
```

```
model:lstm sequence length: 64 layer_dim: 1 hidden size: 32
final loss: 0.002188334590755403, number of epoch: 55


model:lstm sequence length: 64 layer_dim: 2 hidden size: 32
final loss: 0.07838017120957375, number of epoch: 11


model:lstm sequence length: 64 layer_dim: 3 hidden size: 32
final loss: 0.08592137321829796, number of epoch: 11


model:lstm sequence length: 64 layer_dim: 1 hidden size: 128
final loss: 0.0021088375942781568, number of epoch: 100


model:lstm sequence length: 64 layer_dim: 2 hidden size: 128
final loss: 0.08133366703987122, number of epoch: 11


model:lstm sequence length: 64 layer_dim: 3 hidden size: 128
final loss: 0.08304417133331299, number of epoch: 11


model:gru sequence length: 2 layer_dim: 1 hidden size: 2
final loss: 0.0023818729096092284, number of epoch: 100


model:gru sequence length: 2 layer_dim: 2 hidden size: 2
final loss: 0.023731448221951723, number of epoch: 100


model:gru sequence length: 2 layer_dim: 3 hidden size: 2
final loss: 0.003133315942250192, number of epoch: 100


model:gru sequence length: 2 layer_dim: 1 hidden size: 32
final loss: 0.0020543998398352414, number of epoch: 100


model:gru sequence length: 2 layer_dim: 2 hidden size: 32
final loss: 0.0021477317495737225, number of epoch: 100


model:gru sequence length: 2 layer_dim: 3 hidden size: 32
final loss: 0.002515185304218903, number of epoch: 100


model:gru sequence length: 2 layer_dim: 1 hidden size: 128
final loss: 0.0020557274983730167, number of epoch: 65


model:gru sequence length: 2 layer_dim: 2 hidden size: 128
final loss: 0.0021282280795276165, number of epoch: 100


model:gru sequence length: 2 layer_dim: 3 hidden size: 128
final loss: 0.00220199057366699, number of epoch: 100


model:gru sequence length: 16 layer_dim: 1 hidden size: 2
final loss: 0.002376810123678297, number of epoch: 100
```

```
model:gru sequence length: 16 layer_dim: 2 hidden size: 2
final loss: 0.0034049521200358868, number of epoch: 100


model:gru sequence length: 16 layer_dim: 3 hidden size: 2
final loss: 0.1855777995660901, number of epoch: 61


model:gru sequence length: 16 layer_dim: 1 hidden size: 32
final loss: 0.0026503895060159266, number of epoch: 100


model:gru sequence length: 16 layer_dim: 2 hidden size: 32
final loss: 0.0027364250854589045, number of epoch: 100


model:gru sequence length: 16 layer_dim: 3 hidden size: 32
final loss: 0.0034407879575155675, number of epoch: 100


model:gru sequence length: 16 layer_dim: 1 hidden size: 128
final loss: 0.0026776307495310903, number of epoch: 100


model:gru sequence length: 16 layer_dim: 2 hidden size: 128
final loss: 0.0034597795456647873, number of epoch: 100


model:gru sequence length: 16 layer_dim: 3 hidden size: 128
final loss: 0.0037917292211204767, number of epoch: 100


model:gru sequence length: 64 layer_dim: 1 hidden size: 2
final loss: 0.0022816897835582495, number of epoch: 48


model:gru sequence length: 64 layer_dim: 2 hidden size: 2
final loss: 0.12602622993290424, number of epoch: 38


model:gru sequence length: 64 layer_dim: 3 hidden size: 2
final loss: 0.005127181299030781, number of epoch: 23


model:gru sequence length: 64 layer_dim: 1 hidden size: 32
final loss: 0.002007134142331779, number of epoch: 100


model:gru sequence length: 64 layer_dim: 2 hidden size: 32
final loss: 0.002161426527891308, number of epoch: 100


model:gru sequence length: 64 layer_dim: 3 hidden size: 32
final loss: 0.003353759355377406, number of epoch: 100


model:gru sequence length: 64 layer_dim: 1 hidden size: 128
final loss: 0.0020893269684165716, number of epoch: 100


model:gru sequence length: 64 layer_dim: 2 hidden size: 128
final loss: 0.002587254741229117, number of epoch: 100
```

```
model:gru sequence length: 64 layer_dim: 3 hidden size: 128
final loss: 0.0028218089137226343, number of epoch: 100
```

Analysis of the Grid Search

In [24]:
```
# Summary of the grid search
summary_df = pd.DataFrame(summary, columns=["Model", "Sequence length", "Hid
summary_df
#summary_df.to_csv("Result.csv")
```

Out[24]:

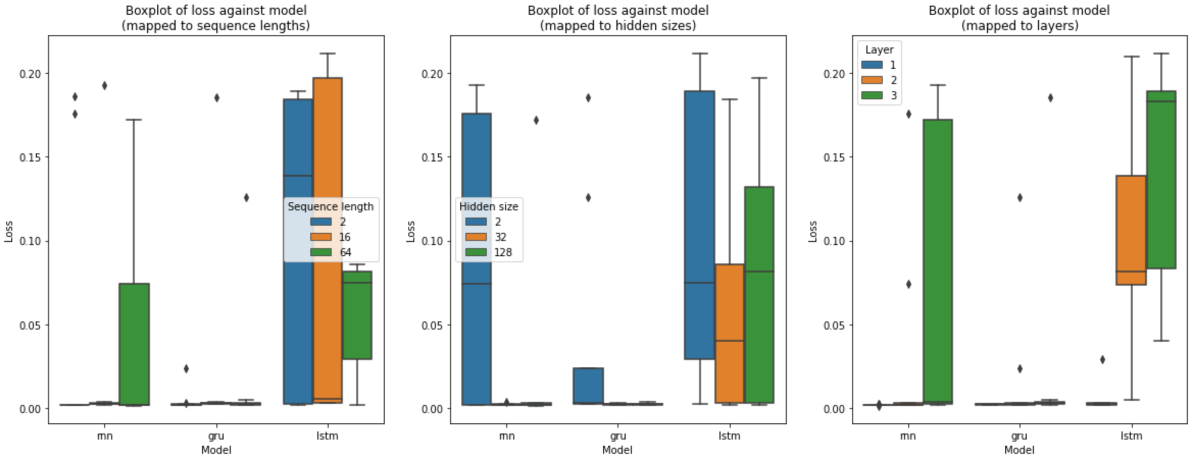
	Model	Sequence length	Hidden size	Layer	Epoch	Loss
24	rnn	64	128	1	100	0.001658
25	rnn	64	128	2	100	0.001804
21	rnn	64	32	1	77	0.001933
18	rnn	64	2	1	98	0.001989
3	rnn	2	32	1	63	0.001996
...	...	...	...	...	...	...
29	lstm	2	2	3	16	0.188977
11	rnn	16	2	3	66	0.192418
44	lstm	16	128	3	13	0.196989
37	lstm	16	2	2	11	0.209488
38	lstm	16	2	3	11	0.211697

81 rows × 6 columns

In [25]:
```
# Mean and SD of the types of the model
for model_type in ["rnn", "lstm", "gru"]:
  loss_distrib = summary_df[summary_df["Model"]== model_type]["Loss"]
  print(f"sum:{loss_distrib.sum()} mean:{loss_distrib.mean()} std:{loss_dist
```

```
sum:0.9226982101681642 mean:0.03417400778400608 std:0.06552526055878212
sum:2.209848379046889 mean:0.0818462362609959 std:0.07895385510851986
sum:0.40092201565857977 mean:0.014848963542910362 std:0.04165954762048193
```

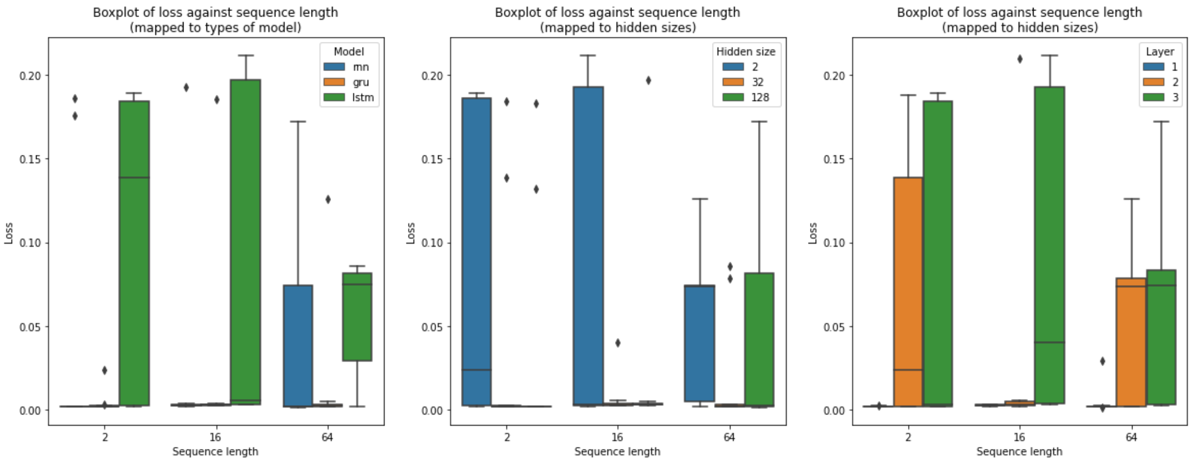
In [26]:
```
# Boxplots of types of the model
fig, ax = plt.subplots(1,3,figsize=[20,7])
sns.boxplot(data=summary_df, x="Model", y="Loss", hue="Sequence length", ax=
sns.boxplot(data=summary_df, x="Model", y="Loss", hue="Hidden size", ax=ax[1
sns.boxplot(data=summary_df, x="Model", y="Loss", hue="Layer", ax=ax[2])
ax[0].set_title("Boxplot of loss against model\n(mapped to sequence lengths)
ax[1].set_title("Boxplot of loss against model\n(mapped to hidden sizes)")
ax[2].set_title("Boxplot of loss against model\n(mapped to layers)")
fig.savefig("model_all.png")
```



In [27]:
```
# Mean and SD of the sequence length
for sequence in [2, 16, 64]:
  loss_distrib = summary_df[summary_df["Sequence length"]== sequence]["Loss"
  print(f"sum:{loss_distrib.sum()} mean:{loss_distrib.mean()} std:{loss_dist
```

```
sum:1.4395211498776916 mean:0.05331559814361 8206 std:0.07948206244497617
sum:1.1023591449775267 mean:0.04082811648064 9136 std:0.0774065160852206
sum:0.9915883100184146 mean:0.03672549296364499 std:0.04762625599883696 4
```

In [28]:
```
# Boxplots of types of the sequence lengths
fig, ax = plt.subplots(1,3,figsize=[20,7])
sns.boxplot(data=summary_df, x="Sequence length", y="Loss", hue="Model", ax=
sns.boxplot(data=summary_df, x="Sequence length", y="Loss", hue="Hidden size
sns.boxplot(data=summary_df, x="Sequence length", y="Loss", hue="Layer", ax=
ax[0].set_title("Boxplot of loss against sequence length\n(mapped to types o
ax[1].set_title("Boxplot of loss against sequence length\n(mapped to hidden
ax[2].set_title("Boxplot of loss against sequence length\n(mapped to hidden
fig.savefig("sequence_all.png")
```

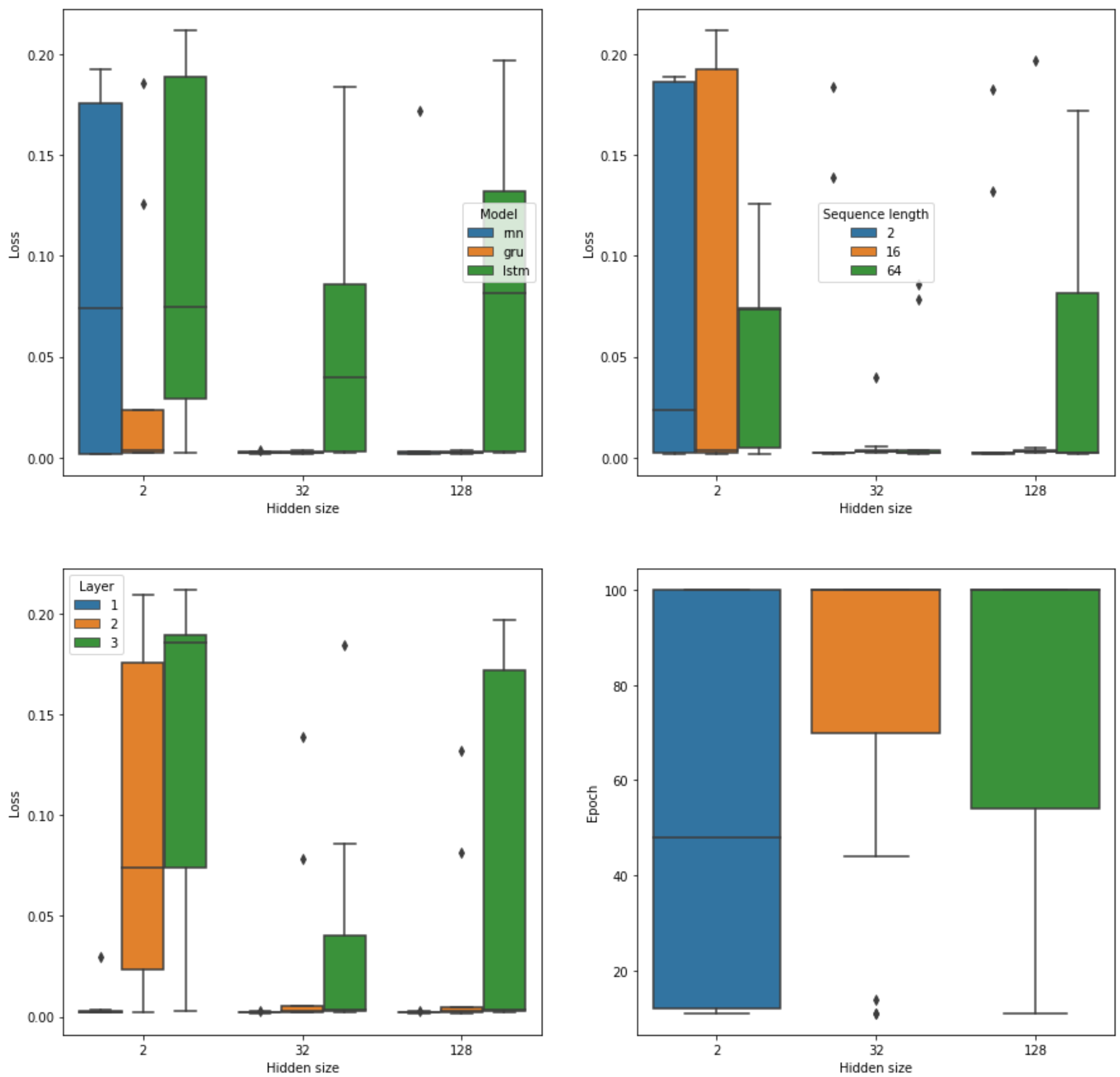


In [29]:
```
# Mean and SD of the hidden sizes
for hidden_size in [2, 32, 128]:
  loss_distrib = summary_df[summary_df["Hidden size"] == hidden_size]["Loss"
  print(f"sum:{loss_distrib.sum()} mean:{loss_distrib.mean()} std:{loss_dist
```

```
sum:2.0462042833678424 mean:0.07578534382843861 std:0.08341923779617891
sum:0.5850831292918883 mean:0.021669745529329196 std:0.046282824810843705
sum:0.9021811922139022 mean:0.03341411823014453 std:0.06283885773148588
```

In [30]:
```
# Boxplots of types of the hidden sizes
fig, ax = plt.subplots(2,2,figsize=[15,15])
sns.boxplot(data=summary_df, x="Hidden size", y="Loss", hue="Model", ax=ax[0
sns.boxplot(data=summary_df, x="Hidden size", y="Loss", hue="Sequence length
sns.boxplot(data=summary_df, x="Hidden size", y="Loss", hue="Layer", ax=ax[1
sns.boxplot(data=summary_df, x="Hidden size", y="Epoch", ax=ax[1][1])
```

Out[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9570642650>
```

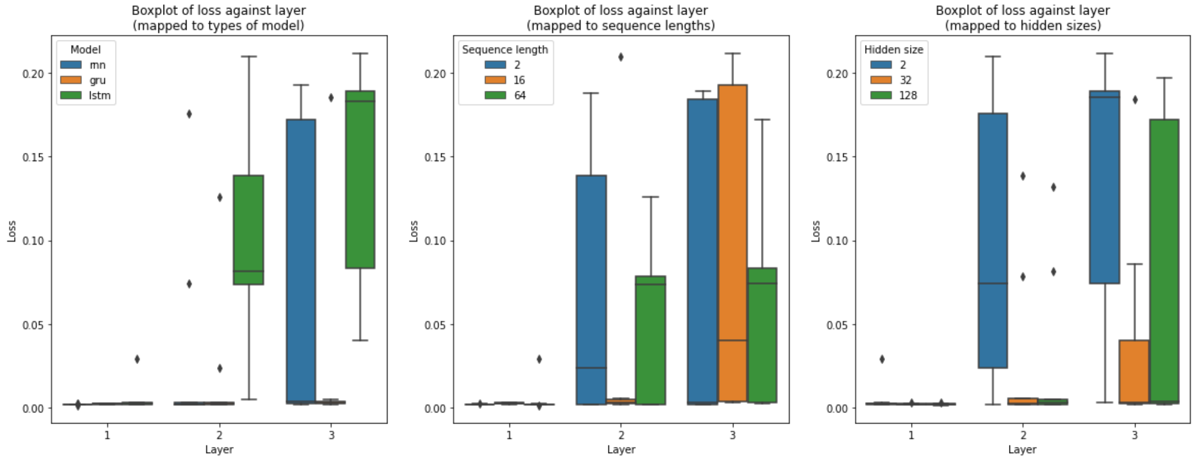


In [31]:
```
# Mean and SD of the number of layers
for layer_num in [1, 2, 3]:
  loss_distrib = summary_df[summary_df["Layer"] == layer_num]["Loss"]
  print(f"sum:{loss_distrib.sum()} mean:{loss_distrib.mean()} std:{loss_dist
```

```
sum:0.08933979683206417 mean:0.003308881364150525 std:0.0052507274205277595
sum:1.34559079297469 mean:0.04983669603609963 std:0.0678820372521258
sum:2.098538015066879 mean:0.07772363018766218 std:0.08462595998515375
```

In [32]:
```
# Boxplots of types of the number of layers
fig, ax = plt.subplots(1,3,figsize=[20,7])
sns.boxplot(data=summary_df, x="Layer", y="Loss", hue="Model", ax=ax[0])
sns.boxplot(data=summary_df, x="Layer", y="Loss", hue="Sequence length", ax=
sns.boxplot(data=summary_df, x="Layer", y="Loss", hue="Hidden size", ax=ax[2
ax[0].set_title("Boxplot of loss against layer\n(mapped to types of model)")
ax[1].set_title("Boxplot of loss against layer\n(mapped to sequence lengths)
ax[2].set_title("Boxplot of loss against layer\n(mapped to hidden sizes)")
#fig.savefig("layer_all.png")
```

Out[32]:
```
Text(0.5, 1.0, 'Boxplot of loss against layer\n(mapped to hidden sizes)')
```



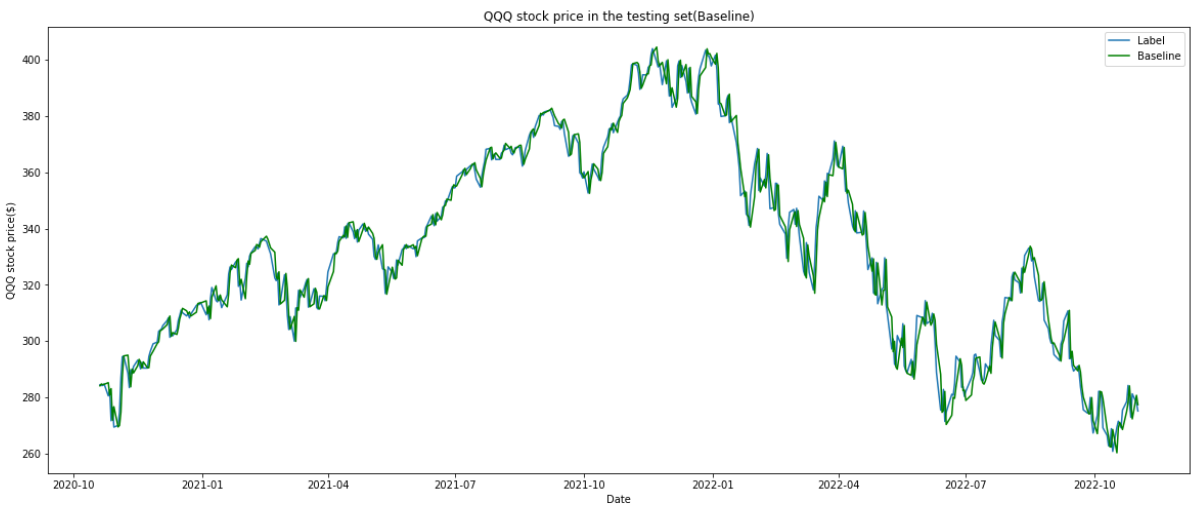
Evaluation

In [34]:
```
# MSE of the label and the baseline
ground_true = testing_set.inverse_transform(testing_set._label) # Unnormaliz
time_axis = pd.to_datetime(testing_set._dataset["Date"][-(ground_true.shape[
baseline_prediction = testing_df["Baseline"][-(ground_true.shape[0])-1:-1] #
mean_squared_error(y_pred=baseline_prediction, y_true=ground_true) # MSE of
```

Out[34]: 26.620108355130274

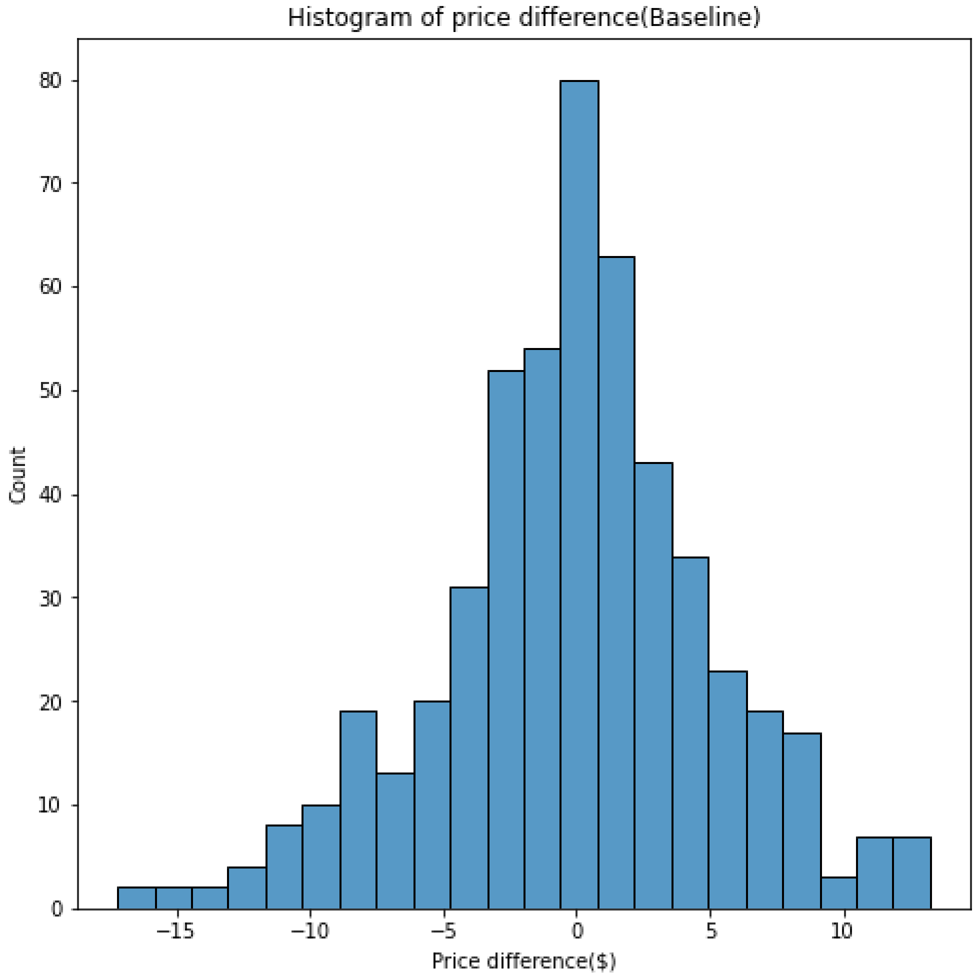
In [35]:
```
# Line plot of labels and baseline predictions
plt.figure(figsize=[20,8])
plt.plot(time_axis, ground_true, label="Label")
plt.plot(time_axis, baseline_prediction, c="g", label="Baseline")
plt.title("QQQ stock price in the testing set(Baseline)")
plt.xlabel("Date")
plt.ylabel("QQQ stock price($)")
plt.legend()
#plt.savefig("baseline prediction")
```

Out[35]: <matplotlib.legend.Legend at 0x7f957096e790>



In [36]:
```
# Distribution of the price difference between labels and baseline predictic
fig, ax = plt.subplots(1,1,figsize=[8,8])
sns.histplot(ground_true-baseline_prediction, ax=ax)
ax.set_title("Histogram of price difference(Baseline)")
ax.set_xlabel("Price difference($)")
```

Out[36]: Text(0.5, 0, 'Price difference($)')

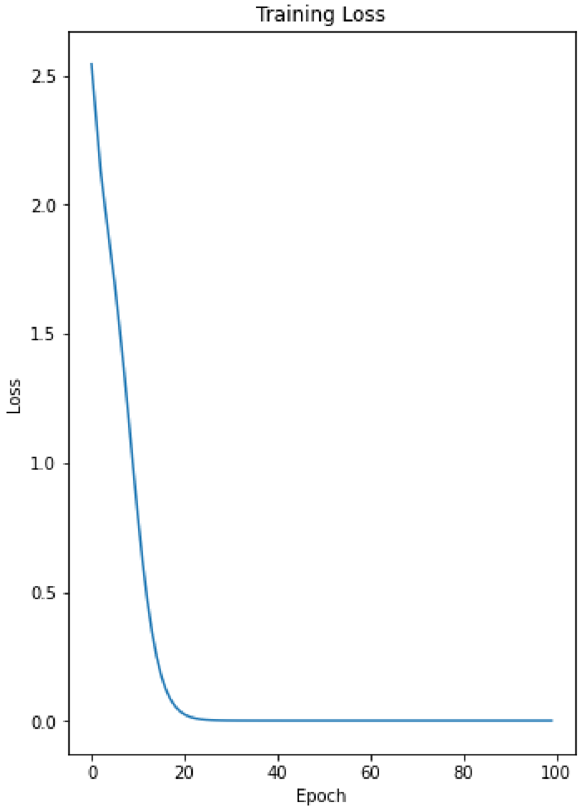


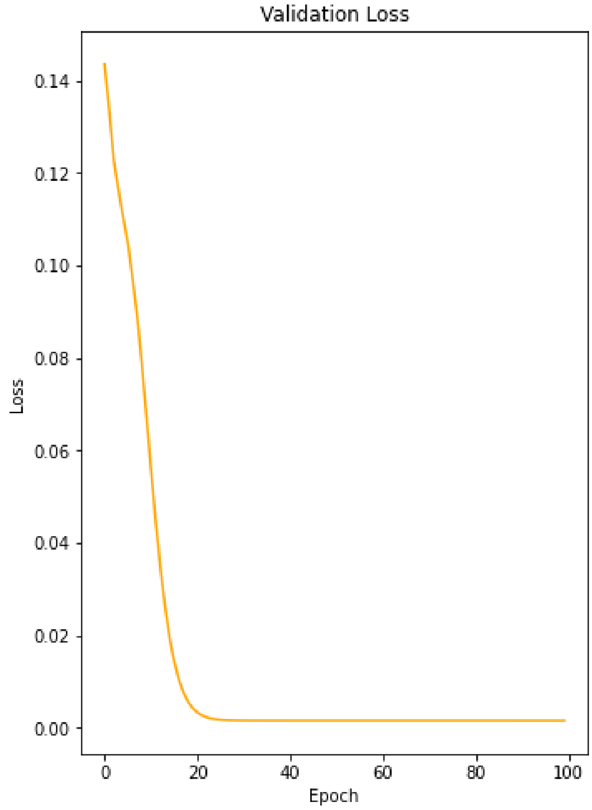
In [37]:

```
# Passing best model into the testing set
deterministic(seed=0)

seq_len = 64
training_set = custom_dataset(dataset=training_df, seq_len=seq_len)
validation_set = custom_dataset(dataset=validation_df, seq_len=seq_len)
testing_set = custom_dataset(dataset=testing_df, seq_len=seq_len)
batch_size = 256
train_loader = DataLoader(dataset=training_set, batch_size=batch_size)
valid_loader = DataLoader(dataset=validation_set, batch_size=batch_size)
test_loader = DataLoader(dataset=testing_set, batch_size=batch_size)
input_dim = 1
hidden_dim = 128
layer_dim = 1
rnn = RNN(input_dim=input_dim, hidden_dim=hidden_dim, layer_dim=layer_dim, s
criterion = nn.MSELoss()
learning_rate = 0.05
optimizer = torch.optim.SGD(rnn.parameters(), lr=learning_rate)
rnn, valid_loss = train(model=rnn, train_data=train_loader, valid_data=valid
                            verbose=False, lr_curve=True)
```

```
final loss: 0.0015854948142077774, number of epoch: 100
```

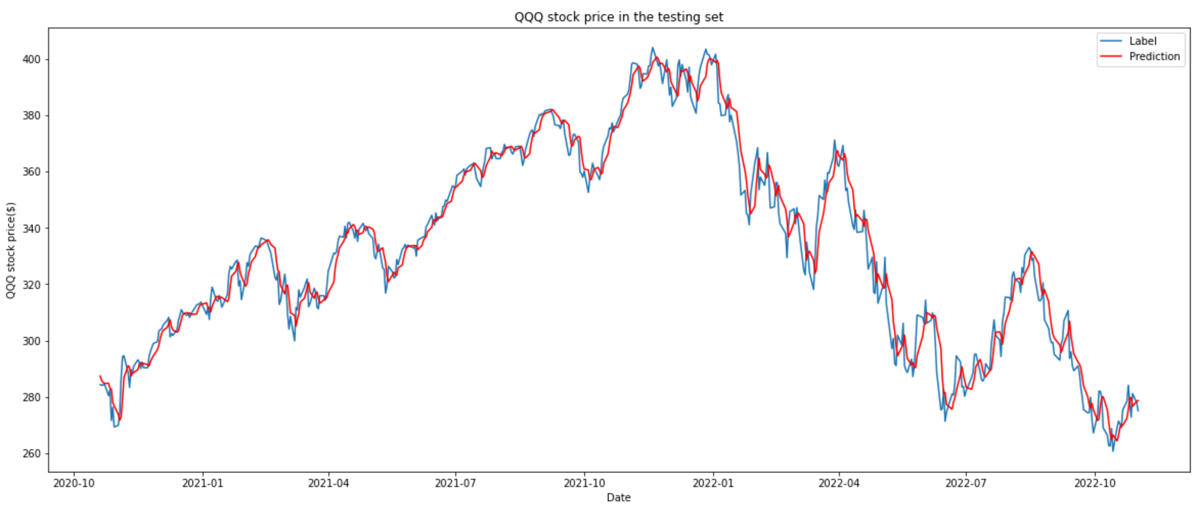




In [38]:
```
# MSE loss of labels and the prediction from the best model
outputs, prediction = evaluate(rnn, test_loader)
predictions = testing_set.inverse_transform(prediction)
mean_squared_error(y_pred=predictions, y_true=ground_true)
```

Out[38]: 34.82002755317491

In [39]:
```
# Line plot of labels and the best model predictions
plt.figure(figsize=[20,8])
ground_true = testing_set.inverse_transform(testing_set._label)
time_axis = pd.to_datetime(testing_set._dataset["Date"][-(ground_true.shape[
plt.plot(time_axis, ground_true, label="Label")
plt.plot(time_axis, predictions, c="r", label="Prediction")
plt.title("QQQ stock price in the testing set")
plt.xlabel("Date")
plt.ylabel("QQQ stock price($)")
plt.legend()
plt.savefig("RNN prediction")
```



In [40]:
```
# Distribution of the price difference between labels and baseline predictio
```

```
fig, ax = plt.subplots(1,1,figsize=[8,8])
sns.histplot(testing_set.inverse_transform(testing_set._label)-predictions,
ax.set_title("Histogram of price difference")
ax.set_xlabel("Price difference($)")
#fig.savefig("price_difference.png")
```

Out[40]: Text(0.5, 0, 'Price difference($)')