## МІНІСТЕРСТВО ОСВІТИ І НАУКИ УКРАЇНИ НАЦІОНАЛЬНИЙ УНІВЕРСИТЕТ "ЛЬВІВСЬКА ПОЛІТЕХНІКА" ІНСТИТУТ КОМП'ЮТЕРНИХ НАУК ТА ІНФОРМАЦІЙНИХ ТЕХНОЛОГІЙ кафедра систем штучного інтелекту



## **3BIT**

про виконання лабораторної роботи №1 з курсу «Проектування систем глибинного навчання» на тему « ПрогнозуваннянаосновіRNN LSTM GRU»

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**Meтa:** Виконати задані завдання за темою ПрогнозуваннянаосновіRNN LSTM GRU.

## Завдання

- Вивчити структуру LSTM та GRU та принцип побудови мережі за допомогою Keras.
- Розібратися з Case1 прогнозування сигналів. Згенерувати свій сигналнабазі sinтa cos, та їх комбінації і спробувати спрогнозувати, оцінити точність.
- Розібрати з задачею прогнозування часових рядів фінансової природизадопомогою LSTM та GRU.
- Досягти кращої точності ніж наведено в прикладі, за рахунок переналаштуваннямережі.

## Виконання роботи:

```
import numpy as np
import pandas as pd
import math
import sklearn
import sklearn.preprocessing
import datetime
import os
import matplotlib.pyplot as plt
%tensorflow_version 1.x
import tensorflow as tf
from keras.layers.recurrent import LSTM
from keras.models import Sequential
from keras.layers import Dense, Dropout
dataset = pd.read_csv('Sin Wave Data Generator.csv')
dataset.head(5)
```

```
Wave
0  0.841471
1  0.873736
2  0.902554
3  0.927809
4  0.949402

dataset["Wave"][:].plot(figsize=(16,4),legend=False)
<matplotlib.axes._subplots.AxesSubplot at 0x7f95d9cd9fd0>
```

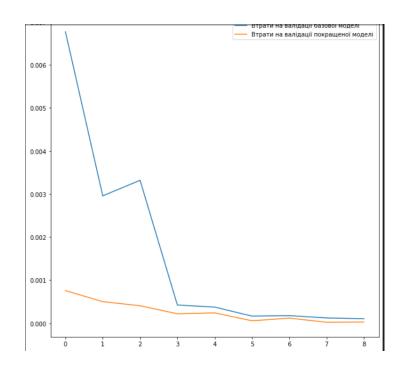
```
def normalise_windows(window_data):
    # A support function to normalize a dataset
    normalised_data = []
    for window in window data:
        normalised_window = [((float(p) / float(window[0])) - 1) for p in window]
        normalised_data.append(normalised_window)
    return normalised data
def load_data(dataset, column, seq_len, normalise_window):
    # A support function to help prepare datasets for an RNN/LSTM/GRU
    data = dataset.loc[:,column]
    sequence_length = seq_len + 1
    result = []
    for index in range(len(data) - sequence_length):
        result.append(data[index: index + sequence_length])
    if normalise window:
        result = normalise_windows(result)
    result = np.array(result)
    #Last 10% is used for validation test, first 90% for training
    row = round(0.9 * result.shape[0])
    train = result[:int(row), :]
    np.random.shuffle(train)
    x_train = train[:, :-1]
    y_train = train[:, -1]
    x_test = result[int(row):, :-1]
    y_test = result[int(row):, -1]
    x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
    x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1))
    return [x_train, y_train, x_test, y_test]
```

```
Enrol_window = 100
feature_train, label_train, feature_test, label_test = load_data(dataset, 'Wave',
Enrol_window, False)
print ('Datasets generated')
model = Sequential()
model.add(LSTM(50, return_sequences=True, input_shape=(feature_train.shape[1],1)))
model.add(Dropout(0.2))
```

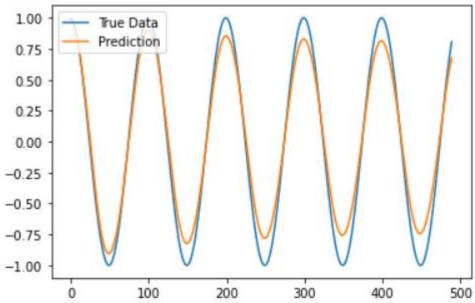
```
model.add(LSTM(100, return_sequences=False))
model.add(Dropout(0.2))
model.add(Dense(1, activation = "linear"))

model.compile(loss='mse', optimizer='adam')
print ('model compiled')
print (model.summary())
Total params: 70,901 Trainable params: 70,901 Non-trainable params: 0
```

```
model = Sequential()
model.add(LSTM(40, return_sequences=True, input_shape=(feature_train.shape[1],1)))
model.add(Dropout(0.2))
model.add(LSTM(70, return sequences=False))
model.add(Dropout(0.2))
model.add(Dense(1, activation = "linear"))
model.compile(loss='mse', optimizer='adam')
print ('model compiled')
print (model.summary())
history adv = model.fit(feature train, label train, batch size=256, epochs=10,
validation_data = (feature_test, label_test))
val_loss = history.history['val_loss']
val_loss_adv = history_adv.history['val_loss']
val_loss = val_loss[1:]
val_loss_adv = val_loss_adv[1:]
epochs_range = range(9)
plt.figure(figsize=(10,10))
plt.plot(epochs_range, val_loss, label='Втрати на валідації базової моделі')
plt.plot(epochs_range, val_loss_adv, label='Втрати на валідації покращеної моделі')
plt.legend(loc='upper right')
plt.title(f'Графіки втрат покращеної моделі')
```



```
from numpy import newaxis
def predict_sequence_full(model, data, window_size):
window
    curr_frame = data[0]
    predicted = []
    for i in range(len(data)):
        predicted.append(model.predict(curr_frame[newaxis,:,:])[0,0])
        curr_frame = curr_frame[1:]
        curr_frame = np.insert(curr_frame, [window_size-1], predicted[-1], axis=0)
    return predicted
def plot_results(predicted_data, true_data):
    fig = plt.figure(facecolor='white')
    ax = fig.add_subplot(111)
    ax.plot(true_data, label='True Data')
    plt.plot(predicted_data, label='Prediction')
    plt.legend(loc='upper left')
    plt.show()
```



\*\*Case 2. NY Stock Price Prediction RNN LSTM GRU\*\*

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt

# tensorflow 1
import tensorflow.compat.v1 as tf1
tf1.disable_v2_behavior()

# tensorflow 2
from tensorflow import keras
from tensorflow.keras import layers

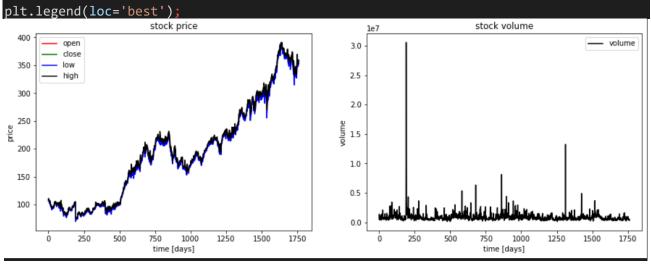
# split data in 80%/10%/10% train/validation/test sets
valid_set_size_percentage = 10
```

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date						
2016-12-30	ZBH	103.309998	103.199997	102.849998	103.930000	973800.0
2016-12-30	ZION	43.070000	43.040001	42.689999	43.310001	1938100.0
2016-12-30	ZTS	53.639999	53.529999	53.270000	53.740002	1701200.0
2016-12-30	AIV	44.730000	45.450001	44.410000	45.590000	1380900.0
2016-12-30	FTV	54.200001	53.630001	53.389999	54.480000	705100.0

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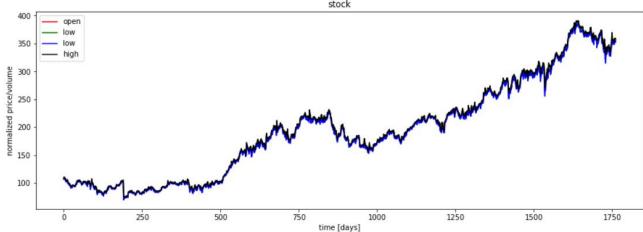
	open	close	low	high	volume
count	851264.000000	851264.000000	851264.000000	851264.000000	8.512640e+05
mean	64.993618	65.011913	64.336541	65.639748	5.415113e+06
std	75.203893	75.201216	74.459518	75.906861	1.249468e+07
min	1.660000	1.590000	1.500000	1.810000	0.000000e+00
25%	31.270000	31.292776	30.940001	31.620001	1.221500e+06
50%	48.459999	48.480000	47.970001	48.959999	2.476250e+06
75%	75.120003	75.139999	74.400002	75.849998	5.222500e+06
max	1584.439941	1578.130005	1549.939941	1600.930054	8.596434e+08

```
plt.figure(figsize=(15, 5));
plt.subplot(1,2,1);
plt.plot(df[df.symbol == 'EQIX'].open.values, color='red', label='open')
plt.plot(df[df.symbol == 'EQIX'].close.values, color='green', label='close')
plt.plot(df[df.symbol == 'EQIX'].low.values, color='blue', label='low')
plt.plot(df[df.symbol == 'EQIX'].high.values, color='black', label='high')
plt.title('stock price')
plt.xlabel('time [days]')
plt.ylabel('price')
plt.legend(loc='best')
#plt.show()
plt.subplot(1,2,2);
plt.plot(df[df.symbol == 'EQIX'].volume.values, color='black', label='volume')
plt.title('stock volume')
plt.xlabel('time [days]')
plt.ylabel('volume')
```



```
# function for min-max normalization of stock
def normalize data(df):
    min_max_scaler = sklearn.preprocessing.MinMaxScaler()
    df['open'] = min_max_scaler.fit_transform(df.open.values.reshape(-1,1))
    df['high'] = min max scaler.fit transform(df.high.values.reshape(-1,1))
    df['low'] = min max scaler.fit transform(df.low.values.reshape(-1,1))
    df['close'] = min_max_scaler.fit_transform(df['close'].values.reshape(-1,1))
    return df
# function to create train, validation, test data given stock data and sequence
def load_data(stock, seq_len):
    data_raw = stock.to_numpy() # convert to numpy array
    data = []
    # create all possible sequences of length seq len
    for index in range(len(data_raw) - seq_len):
        data.append(data raw[index: index + seq len])
    data = np.array(data);
    valid_set_size = int(np.round(valid_set_size_percentage/100*data.shape[0]));
    test_set_size = int(np.round(test_set_size_percentage/100*data.shape[0]));
    train_set_size = data.shape[0] - (valid_set_size + test_set_size);
    x train = data[:train set size,:-1,:]
    y_train = data[:train_set_size,-1,:]
    x_valid = data[train_set_size:train_set_size+valid_set_size,:-1,:]
    y_valid = data[train_set_size:train_set_size+valid_set_size,-1,:]
    x_test = data[train_set_size+valid_set_size:,:-1,:]
    y_test = data[train_set_size+valid_set_size:,-1,:]
    return [x_train, y_train, x_valid, y_valid, x_test, y_test]
# choose one stock
df stock = df[df.symbol == 'EQIX'].copy()
df stock.drop(['symbol'],1,inplace=True)
```

```
df stock.drop(['volume'],1,inplace=True)
cols = list(df_stock.columns.values)
print('df_stock.columns.values = ', cols)
# normalize stock
df_stock_norm = df_stock.copy()
df_stock_norm = normalize_data(df_stock_norm)
seq len = 20 # choose sequence length
x_train, y_train, x_valid, y_valid, x_test, y_test = load_data(df_stock_norm,
seq_len)
print('x_train.shape = ',x_train.shape)
print('y_train.shape = ', y_train.shape)
print('x_valid.shape = ',x_valid.shape)
print('y_valid.shape = ', y_valid.shape)
print('x_test.shape = ', x_test.shape)
print('y_test.shape = ',y_test.shape)
plt.figure(figsize=(15, 5))
plt.plot(df stock.open.values, color='red', label='open')
plt.plot(df stock.close.values, color='green', label='low')
plt.plot(df_stock.low.values, color='blue', label='low')
plt.plot(df_stock.high.values, color='black', label='high')
plt.title('stock')
plt.xlabel('time [days]')
plt.ylabel('normalized price/volume')
plt.legend(loc='best')
plt.show()
                                           stock
```



```
## Basic Cell RNN in tensorflow

index_in_epoch = 0;
perm_array = np.arange(x_train.shape[0])
np.random.shuffle(perm_array)

# function to get the next batch
def get_next_batch(batch_size):
    global index_in_epoch, x_train, perm_array
    start = index_in_epoch
```

```
index in epoch += batch size
    if index_in_epoch > x_train.shape[0]:
        np.random.shuffle(perm_array) # shuffle permutation array
        start = 0 # start next epoch
        index_in_epoch = batch_size
    end = index in epoch
    return x_train[perm_array[start:end]], y_train[perm_array[start:end]]
# parameters
n_steps = seq_len-1
n_{inputs} = 4
n neurons = 200
n_{outputs} = 4
n_{ayers} = 2
learning_rate = 0.001
batch size = 50
n = 100
train_set_size = x_train.shape[0]
test_set_size = x_test.shape[0]
tf.reset_default_graph()
X = tf.placeholder(tf.float32, [None, n_steps, n_inputs])
y = tf.placeholder(tf.float32, [None, n_outputs])
# use Basic RNN Cell
layers = [tf.contrib.rnn.BasicRNNCell(num_units=n_neurons, activation=tf.nn.elu)
          for layer in range(n_layers)]
multi_layer_cell = tf.contrib.rnn.MultiRNNCell(layers)
rnn_outputs, states = tf.nn.dynamic_rnn(multi_layer_cell, X, dtype=tf.float32)
stacked rnn outputs = tf.reshape(rnn outputs, [-1, n neurons])
stacked_outputs = tf.layers.dense(stacked_rnn_outputs, n_outputs)
outputs = tf.reshape(stacked_outputs, [-1, n_steps, n_outputs])
outputs = outputs[:,n_steps-1,:] # keep only last output of sequence
loss = tf.reduce_mean(tf.square(outputs - y)) # loss function = mean squared error
optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate)
training_op = optimizer.minimize(loss)
list_mse_valid = []
# run graph
with tf.Session() as sess:
    sess.run(tf.global variables initializer())
    for iteration in range(int(n_epochs*train_set_size/batch_size)):
        x_batch, y_batch = get_next_batch(batch_size) # fetch the next training
batch
        sess.run(training_op, feed_dict={X: x_batch, y: y_batch})
        if iteration % int(5*train_set_size/batch_size) == 0:
            mse_train = loss.eval(feed_dict={X: x_train, y: y_train})
```

```
mse valid = loss.eval(feed dict={X: x valid, y: y valid})
            list_mse_valid.append(mse_valid)
            print('%.2f epochs: MSE train/valid = %.6f/%.6f'%(
                iteration*batch_size/train_set_size, mse_train, mse_valid))
    y_train_pred = sess.run(outputs, feed_dict={X: x_train})
    y_valid_pred = sess.run(outputs, feed_dict={X: x_valid})
    y_test_pred = sess.run(outputs, feed_dict={X: x test})
ft = 0 # 0 = open, 1 = close, 2 = highest, 3 = lowest
## show predictions
plt.figure(figsize=(15, 5));
plt.subplot(1,2,1);
plt.plot(np.arange(y_train.shape[0]), y_train[:,ft], color='blue', label='train
target')
plt.plot(np.arange(y_train.shape[0], y_train.shape[0]+y_valid.shape[0]),
y_valid[:,ft],
         color='gray', label='valid target')
plt.plot(np.arange(y_train.shape[0]+y_valid.shape[0],
                   y_train.shape[0]+y_test.shape[0]+y_test.shape[0]),
         y_test[:,ft], color='black', label='test target')
plt.plot(np.arange(y_train_pred.shape[0]),y_train_pred[:,ft], color='red',
         label='train prediction')
plt.plot(np.arange(y_train_pred.shape[0],
y_train_pred.shape[0]+y_valid_pred.shape[0]),
         y_valid_pred[:,ft], color='orange', label='valid prediction')
plt.plot(np.arange(y_train_pred.shape[0]+y_valid_pred.shape[0],
                   y_train_pred.shape[0]+y_valid_pred.shape[0]+y_test_pred.shape[0]
),
         y_test_pred[:,ft], color='green', label='test prediction')
plt.title('past and future stock prices')
plt.xlabel('time [days]')
plt.ylabel('normalized price')
plt.legend(loc='best');
plt.subplot(1,2,2);
plt.plot(np.arange(y_train.shape[0], y_train.shape[0]+y_test.shape[0]),
         y_test[:,ft], color='black', label='test target')
plt.plot(np.arange(y_train_pred.shape[0],
y_train_pred.shape[0]+y_test_pred.shape[0]),
         y_test_pred[:,ft], color='green', label='test prediction')
plt.title('future stock prices')
```

```
plt.xlabel('time [days]')
plt.ylabel('normalized price')
plt.legend(loc='best');
corr_price_development_train = np.sum(np.equal(np.sign(y_train[:,1]-y_train[:,0]),
             np.sign(y_train_pred[:,1]-y_train_pred[:,0])).astype(int)) /
y_train.shape[0]
corr_price_development_valid = np.sum(np.equal(np.sign(y_valid[:,1]-y_valid[:,0]),
             np.sign(y_valid_pred[:,1]-y_valid_pred[:,0])).astype(int)) /
y_valid.shape[0]
corr price development test = np.sum(np.equal(np.sign(y test[:,1]-y test[:,0]),
             np.sign(y_test_pred[:,1]-y_test_pred[:,0])).astype(int)) /
y_test.shape[0]
print('correct sign prediction for close - open price for train/valid/test:
%.2f/%.2f/%.2f'%(
    corr_price_development_train, corr_price_development_valid,
corr price development test))
               past and future stock prices
                                                               future stock prices
  1.0

    train target

                                               1.00

    test target
```



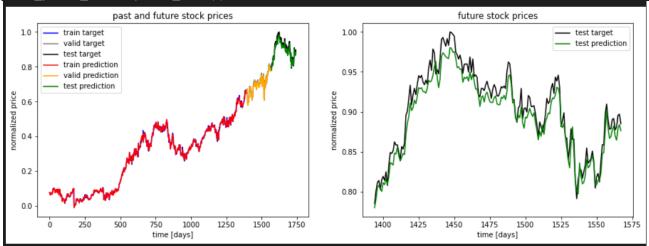


```
## Basic Cell RNN in tensorflow
index in epoch = 0;
perm_array = np.arange(x_train.shape[0])
np.random.shuffle(perm_array)
# function to get the next batch
def get_next_batch(batch_size):
    global index_in_epoch, x_train, perm_array
    start = index_in_epoch
    index_in_epoch += batch_size
    if index_in_epoch > x_train.shape[0]:
        np.random.shuffle(perm_array) # shuffle permutation array
        start = 0 # start next epoch
        index_in_epoch = batch_size
    end = index_in_epoch
    return x_train[perm_array[start:end]], y_train[perm_array[start:end]]
# parameters
```

```
n \text{ steps} = \text{seq len-1}
n_{inputs} = 4
n neurons = 180
n_outputs = 4
n layers = 2
dropout rate = 0
learning_rate = 0.001
batch size = 50
n epochs = 100
train_set_size = x_train.shape[0]
test_set_size = x_test.shape[0]
tf.reset_default_graph()
X = tf.placeholder(tf.float32, [None, n_steps, n_inputs])
y = tf.placeholder(tf.float32, [None, n_outputs])
# use Basic RNN Cell
layers = []
for i in range(n_layers):
    layers.append(tf.contrib.rnn.DropoutWrapper(tf.contrib.rnn.BasicRNNCell(num uni
ts=n_neurons, activation=tf.nn.elu),
                                              output_keep_prob=1-dropout_rate))
multi_layer_cell = tf.contrib.rnn.MultiRNNCell(layers)
rnn_outputs, states = tf.nn.dynamic_rnn(multi_layer_cell, X, dtype=tf.float32)
stacked_rnn_outputs = tf.reshape(rnn_outputs, [-1, n_neurons])
stacked_outputs = tf.layers.dense(stacked_rnn_outputs, n_outputs)
outputs = tf.reshape(stacked_outputs, [-1, n_steps, n_outputs])
outputs = outputs[:,n_steps-1,:] # keep only last output of sequence
loss = tf.reduce_mean(tf.square(outputs - y)) # loss function = mean squared error
optimizer = tf.train.AdamOptimizer(learning rate=learning rate)
training_op = optimizer.minimize(loss)
list_mse_valid_adv = []
# run graph
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    for iteration in range(int(n_epochs*train_set_size/batch_size)):
        x_batch, y_batch = get_next_batch(batch_size) # fetch the next training
batch
        sess.run(training_op, feed_dict={X: x_batch, y: y_batch})
        if iteration % int(5*train_set_size/batch_size) == 0:
            mse_train = loss.eval(feed_dict={X: x_train, y: y_train})
            mse valid = loss.eval(feed dict={X: x valid, y: y valid})
            list mse valid adv.append(mse valid)
            print('%.2f epochs: MSE train/valid = %.6f/%.6f'%(
                iteration*batch_size/train_set_size, mse_train, mse_valid))
    y_train_pred = sess.run(outputs, feed_dict={X: x_train})
    y_valid_pred = sess.run(outputs, feed_dict={X: x_valid})
```

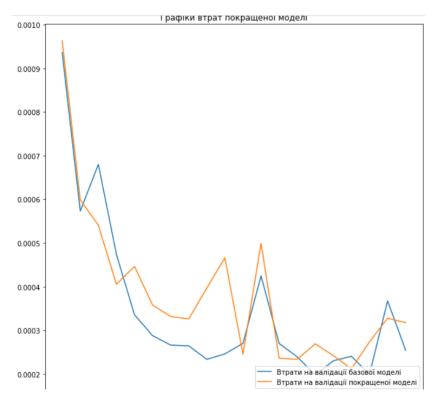
```
y test pred = sess.run(outputs, feed dict={X: x test})
ft = 0 # 0 = open, 1 = close, 2 = highest, 3 = lowest
## show predictions
plt.figure(figsize=(15, 5));
plt.subplot(1,2,1);
plt.plot(np.arange(y_train.shape[0]), y_train[:,ft], color='blue', label='train
target')
plt.plot(np.arange(y_train.shape[0], y_train.shape[0]+y_valid.shape[0]),
y_valid[:,ft],
         color='gray', label='valid target')
plt.plot(np.arange(y_train.shape[0]+y_valid.shape[0],
                   y_train.shape[0]+y_test.shape[0]+y_test.shape[0]),
         y_test[:,ft], color='black', label='test target')
plt.plot(np.arange(y_train_pred.shape[0]),y_train_pred[:,ft], color='red',
         label='train prediction')
plt.plot(np.arange(y_train_pred.shape[0],
y_train_pred.shape[0]+y_valid_pred.shape[0]),
         y_valid_pred[:,ft], color='orange', label='valid prediction')
plt.plot(np.arange(y_train_pred.shape[0]+y_valid_pred.shape[0],
                   y_train_pred.shape[0]+y_valid_pred.shape[0]+y_test_pred.shape[0]
),
         y_test_pred[:,ft], color='green', label='test prediction')
plt.title('past and future stock prices')
plt.xlabel('time [days]')
plt.ylabel('normalized price')
plt.legend(loc='best');
plt.subplot(1,2,2);
plt.plot(np.arange(y_train.shape[0], y_train.shape[0]+y_test.shape[0]),
         y_test[:,ft], color='black', label='test target')
plt.plot(np.arange(y_train_pred.shape[0],
y_train_pred.shape[0]+y_test_pred.shape[0]),
         y_test_pred[:,ft], color='green', label='test prediction')
plt.title('future stock prices')
plt.xlabel('time [days]')
plt.ylabel('normalized price')
plt.legend(loc='best');
corr_price_development_train = np.sum(np.equal(np.sign(y_train[:,1]-y_train[:,0]),
            np.sign(y_train_pred[:,1]-y_train_pred[:,0])).astype(int)) /
y_train.shape[0]
```

```
corr price_development_valid = np.sum(np.equal(np.sign(y_valid[:,1]-y_valid[:,0]),
             np.sign(y_valid_pred[:,1]-y_valid_pred[:,0])).astype(int)) /
y_valid.shape[0]
corr_price_development_test = np.sum(np.equal(np.sign(y_test[:,1]-y_test[:,0]),
             np.sign(y_test_pred[:,1]-y_test_pred[:,0])).astype(int)) /
y_test.shape[0]
print('correct sign prediction for close - open price for train/valid/test:
%.2f/%.2f/%.2f'%(
    corr_price_development_train, corr_price_development_valid,
corr price development test))
               past and future stock prices
                                                                  future stock prices
                                                 1.00
  1.0
        train target
                                                                                   test target
        valid target
                                                                                   test prediction
        test target
```



```
val_loss = list_mse_valid
val_loss_adv = list_mse_valid_adv
val_loss = val_loss[1:]
val_loss_adv = val_loss_adv[1:]
epochs_range = range(20)

plt.figure(figsize=(10,10))
plt.plot(epochs_range, val_loss, label='Втрати на валідації базової моделі')
plt.plot(epochs_range, val_loss_adv, label='Втрати на валідації покращеної моделі')
plt.legend(loc='lower right')
plt.title(f'Графіки втрат покращеної моделі')
```



**Висновок:** На даній лабораторній роботі, виконав поставлені завдання а саме Вивчити структуру LSTM та GRU та принцип побудови мережі, розібрався з Case1 — прогнозування сигналів, розібрав з задачею прогнозування часових рядів, досягнув кращої точності ніж наведено в прикладі.