#### **Importing Packages**

```
In [1]: import pandas as pd
    import numpy as np
    from keras.models import Sequential
    from keras.layers import LSTM, Dense, Bidirectional, Dropout
    from sklearn.preprocessing import MinMaxScaler
    from keras.optimizers import Adam
    import matplotlib.pyplot as plt
```

## **Data Preprocessing**

```
In [2]: | df = pd.read excel('input copy full 2 (copy).xlsx')
In [3]: df.head()
Out[3]:
            Unnamed: 0 Unnamed: 1
                                    Unnamed: 2
         0
             2023-02-28
                             NaN 04 06 10 26 30
         1
             2022-02-27
                             NaN 01 03 18 26 27
            2022-02-26
                             NaN 13 17 18 50 60
         2
             2022-02-25
                             NaN 09 12 35 35 56
             2022-02-24
                             NaN 15 21 39 45 49
In [4]: |df.info()
         <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 1773 entries, 0 to 1772
        Data columns (total 3 columns):
              Column
                          Non-Null Count Dtype
          0
              Unnamed: 0 1773 non-null
                                           datetime64[ns]
          1
              Unnamed: 1 0 non-null
                                           float64
              Unnamed: 2 1773 non-null
                                           obiect
        dtypes: datetime64[ns](1), float64(1), object(1)
        memory usage: 41.7+ KB
In [5]: # split the numbers column into separate columns
        numbers_df = df['Unnamed: 2'].str.split(expand=True)
In [6]: | numbers_df = numbers_df.astype(int)
```

```
In [7]: numbers df.describe()
 Out[7]:
                                                  2
                          0
                                      1
                                                             3
                                                                         4
           count 1773.000000 1773.000000 1773.000000 1773.000000
                                                                1773.000000
                   10.238579
                               20.166385
                                           30.358150
                                                      40.503666
           mean
                                                                  50.687535
                               10.339112
                                           11.019518
             std
                    8.142567
                                                      10.644396
                                                                   8.242819
                    1.000000
                                2.000000
                                           4.000000
                                                       6.000000
                                                                  14.000000
            min
            25%
                    4.000000
                               12.000000
                                           22.000000
                                                      34.000000
                                                                  46.000000
            50%
                    8.000000
                               19.000000
                                           30.000000
                                                      42.000000
                                                                  53.000000
            75%
                   15.000000
                               27.000000
                                           39.000000
                                                      49.000000
                                                                  57.000000
                   46.000000
                               56.000000
                                           58.000000
                                                      59.000000
                                                                  60.000000
            max
 In [8]: # normalize the data
          scaler = MinMaxScaler(feature range=(0, 1))
          numbers df = scaler.fit transform(numbers df)
 In [9]: # split the data into training and testing sets
          train size = int(len(numbers df) * 0.7)
          train_data = numbers_df[:train_size, :]
          test data = numbers df[train size:, :]
In [10]: | def create_dataset(dataset, look_back=1):
              dataX, dataY = [], []
              for i in range(len(dataset) - look back):
                   a = dataset[i:(i + look_back), :]
                   dataX.append(a)
                   dataY.append(dataset[i + look_back, :])
              return np.array(dataX), np.array(dataY)
In [11]: # create the training and testing datasets
          look\ back = 5
          trainX, trainY = create_dataset(train_data, look_back)
          testX, testY = create_dataset(test_data, look_back)
```

### **Model Training and Testing**

```
In [12]: # define the model architecture
    model = Sequential()
    model.add(LSTM(units=50, return_sequences=True, input_shape=(5, 5)))
    model.add(LSTM(units=50))
# Adding a first Dropout Layer
    model.add(Dropout(0.2))
# Adding the first output Layer
    model.add(Dense(59))
    model.add(Dropout(0.2))
    model.add(Dense(units=5))

# compile the model
    model.compile(optimizer=Adam(learning_rate= 0.00001 ), loss ='mse', metrics=['model.summary()
```

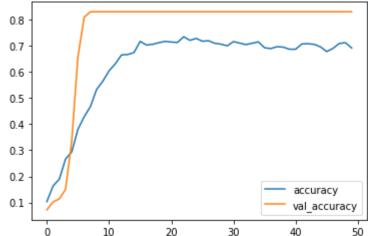
Model: "sequential"

Layer (type)	Output Shape	Param # 
lstm (LSTM)	(None, 5, 50)	11200
lstm_1 (LSTM)	(None, 50)	20200
dropout (Dropout)	(None, 50)	0
dense (Dense)	(None, 59)	3009
dropout_1 (Dropout)	(None, 59)	0
dense_1 (Dense)	(None, 5)	300

------

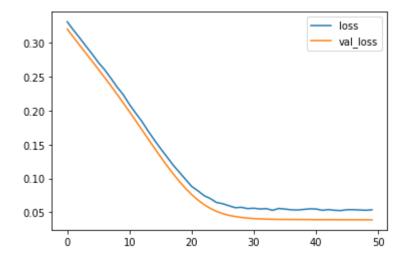
Total params: 34,709 Trainable params: 34,709 Non-trainable params: 0

```
In [13]: # train the model
       history = model.fit(trainX, trainY, validation data =(testX, testY), epochs=50
       Epoch 1/50
       uracy: 0.1036 - val loss: 0.3204 - val accuracy: 0.0721
       Epoch 2/50
       39/39 [========== ] - 1s 13ms/step - loss: 0.3189 - acc
       uracy: 0.1634 - val loss: 0.3084 - val accuracy: 0.1025
       Epoch 3/50
       uracy: 0.1893 - val_loss: 0.2965 - val_accuracy: 0.1139
       Epoch 4/50
       39/39 [========== ] - 1s 17ms/step - loss: 0.2953 - acc
       uracy: 0.2662 - val loss: 0.2848 - val accuracy: 0.1499
       Epoch 5/50
       uracy: 0.2937 - val_loss: 0.2731 - val_accuracy: 0.3359
       Epoch 6/50
       39/39 [========== ] - 1s 16ms/step - loss: 0.2712 - acc
       uracy: 0.3803 - val loss: 0.2611 - val accuracy: 0.6584
       Epoch 7/50
       20/20 [
                                                        ~ ~~~~
In [18]: test loss, test acc = model.evaluate(testX, testY)
       print('Test accuracy:', test_acc)
       17/17 [=============== ] - 0s 4ms/step - loss: 0.0389 - accurac
       y: 0.8292
       Test accuracy: 0.8292220234870911
In [19]: history_df = pd.DataFrame(history.history)
       history df[['accuracy', 'val accuracy']].plot()
Out[19]: <AxesSubplot:>
```



```
In [20]: history_df = pd.DataFrame(history.history)
history_df[['loss', 'val_loss']].plot()
```

#### Out[20]: <AxesSubplot:>



# **Prediction for Next Sequence**

```
In [21]: # use the model to predict the sequence of numbers
    last_numbers = numbers_df[-5:]
    last_numbers = np.reshape(last_numbers, (1, 5, 5))
    predicted_numbers = model.predict(last_numbers)
    predicted_numbers = scaler.inverse_transform(predicted_numbers)
    predicted_numbers = [int(i) for i in predicted_numbers[0]]

    print('Predicted next Sequence:', predicted_numbers)
```