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Лабораторна робота №6

Основи застосування повнозв’язних мереж для задач регресії

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Мета: дізнатися, як TensorFlow може бути використаний для побудови нейронних мереж з метою реалізації регресійних задач.

Варіант: 15 – dataset “CSM (Conventional and Social Media Movies) Dataset 2014 and 2015 Data Set” (https://archive.ics.uci.edu/ml/machine-learning-databases/00424/)

Data Set Characteristics:	Multivariate	Number of Instances:	217	Area:	Computer
Attribute Characteristics:	Integer	Number of Attributes:	12	Date Donated	2017-10-11
Associated Tasks:	Classification, Regression	Missing Values?	Yes	Number of Web Hits:	49285

Хід виконання роботи:

```
[1] !pip install -q seaborn
```

```
[2] from sklearn.preprocessing import MinMaxScaler
    import keras
    from keras.models import Sequential,Model

    from __future__ import absolute_import, division, print_function, unicode_literals
    import pathlib
    import matplotlib.pyplot as plt
    %matplotlib inline
    import pandas as pd
    import numpy as np
    import seaborn as sns
    import tensorflow as tf
    from tensorflow import keras
    from tensorflow.keras import layers
```

```
[3] # connecting to gdrive
    from google.colab import drive
    drive.mount('/content/gdrive', force_remount=True)
    gdrive_path = f"/content/gdrive/MyDrive/ds/"

    Mounted at /content/gdrive
```

CSM (Conventional and Social Media Movies) Dataset 2014 and 2015 Data Set source

12 features categorized as conventional and social media features. Both conventional features, collected from movies databases on Web as well as social media features(YouTube,Twitter).

```
[4] # reading a specific sheet from the dataset Excel file into pandas dataframe
    data = pd.read_excel('/content/gdrive/MyDrive/ds/2014 and 2015 CSM dataset.xlsx',
                         sheet_name='Sheet1')
    # show general info about the dataframe
    data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 231 entries, 0 to 230
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Movie               231 non-null    object
 1   Year                231 non-null    int64
 2   Ratings             231 non-null    float64
 3   Genre               231 non-null    int64
 4   Gross               231 non-null    int64
 5   Budget              230 non-null    float64
 6   Screens             221 non-null    float64
 7   Sequel              231 non-null    int64
 8   Sentiment           231 non-null    int64
 9   Views               231 non-null    int64
 10  Likes               231 non-null    int64
 11  Dislikes            231 non-null    int64
 12  Comments            231 non-null    int64
 13  Aggregate Followers 196 non-null    float64
dtypes: float64(4), int64(9), object(1)
memory usage: 25.4+ KB
```

```
[5] # show first 5 rows of the dataframe
    data.head()
```

	Movie	Year	Ratings	Genre	Gross	Budget	Screens	Sequel	Sentiment	Views	Likes	Dislikes	Comments	Aggregate Followers
0	13 Sins	2014	6.3	8	9130	4000000.0	45.0	1	0	3280543	4632	425	636	1120000.0
1	22 Jump Street	2014	7.1	1	192000000	50000000.0	3306.0	2	2	583289	3465	61	186	12350000.0
2	3 Days to Kill	2014	6.2	1	30700000	28000000.0	2872.0	1	0	304861	328	34	47	483000.0
3	300: Rise of an Empire	2014	6.3	1	106000000	110000000.0	3470.0	2	0	452917	2429	132	590	568000.0
4	A Haunted House 2	2014	4.7	8	17300000	3500000.0	2310.0	2	0	3145573	12163	610	1082	1923800.0

```
[6] # counting total number of gaps per column
    data.isnull().sum()
```

```
Movie                   0
Year                    0
Ratings                 0
Genre                   0
Gross                   0
Budget                  1
Screens                10
Sequel                  0
Sentiment               0
Views                   0
Likes                   0
Dislikes                0
Comments                0
Aggregate Followers    35
dtype: int64
```

```
[7] # computing the mean of each column with numerical values
    means = data.iloc[:, 1:].mean()
    # filling gaps with the mean value of each column
    data.iloc[:, 1:] = data.iloc[:, 1:].fillna(means)
    # checking total number of gaps per column after the filling
    data.isnull().sum()
```

```
Movie                  0
Year                   0
Ratings                0
Genre                  0
Gross                  0
Budget                 0
Screens                0
Sequel                 0
Sentiment              0
Views                  0
Likes                  0
Dislikes               0
Comments               0
Aggregate Followers    0
dtype: int64
```

```
[8] # getting lists of dataset columns by their numerical data type
    float_cols = data.select_dtypes(include=['float64']).columns.tolist()
    int_cols = data.select_dtypes(include=['int64']).columns.tolist()
    print(f"Continuous data columns: {float_cols}")
    print(f"Discrete data columns: {int_cols}")
```

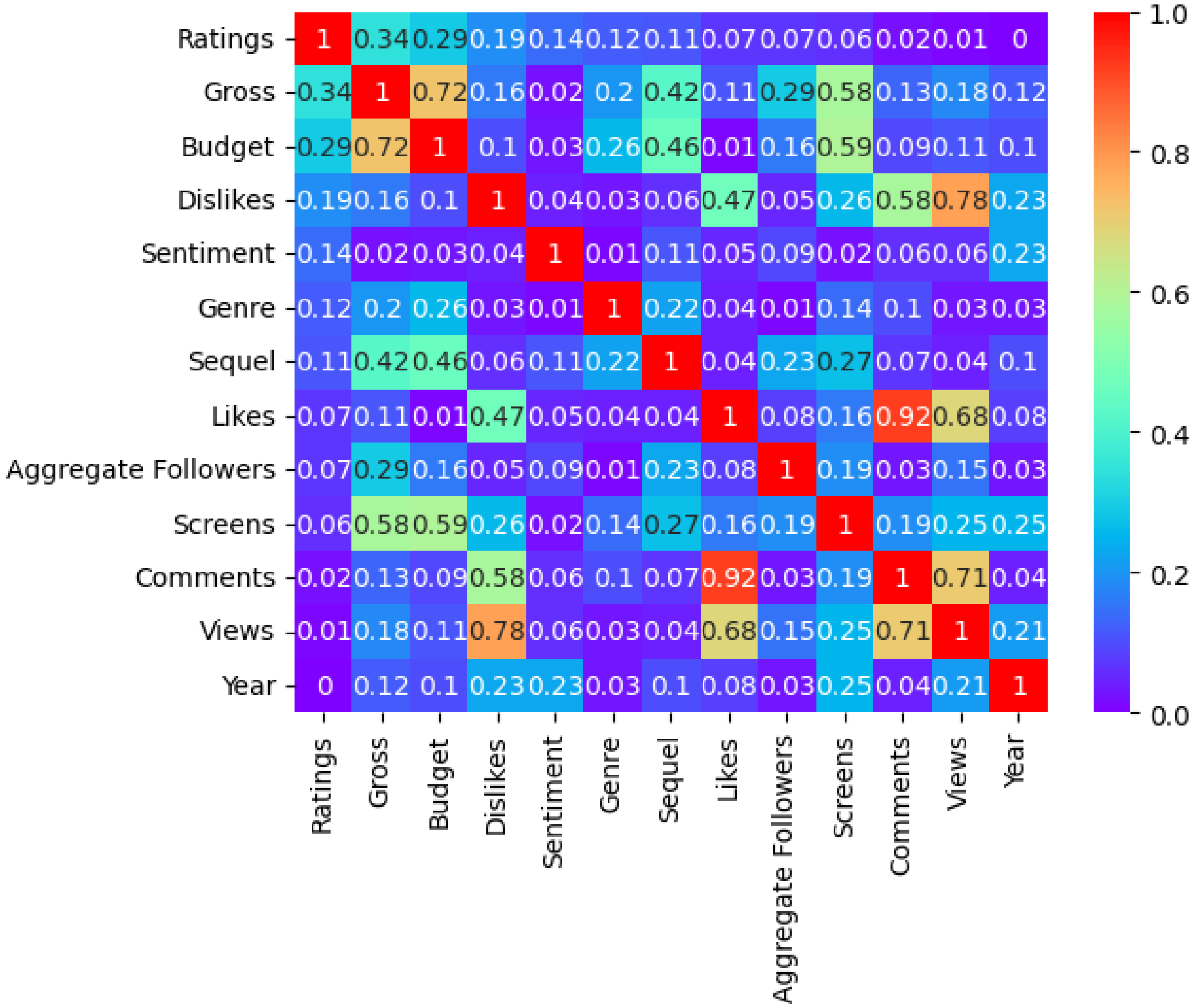
```
nuous data columns: ['Ratings', 'Budget', 'Screens', 'Aggregate Followers']
ete data columns: ['Year', 'Genre', 'Gross', 'Sequel', 'Sentiment', 'Views', 'Likes', 'Dislikes', 'Comments']
```

Based on the formed column lists, the Movie title represented by string values is the only one missing.

As for the original data type of the float columns, all except the Ratings should be converted to the discrete integer type due to their quantitative nature. However, considering the input data normalization, it's not necessary.

Moreover, the Ratings column is defined as a target variable for the current regression task.

```
[9] # selecting the target column label
    target_col = float_cols.pop(0)
    # calculating the correlation strength between the target column and all other
    # columns in the dataframe subset selected for the numerical analysis
    tcs = data.corr().abs()[target_col].sort_values(ascending=False)
    # reordering columns in the selected dataframe
    data_num = data.loc[:, list(tcs.index)]
    # creating a heatmap displaying the correlation matrix
    sns.heatmap(data_num.corr().abs().round(2), annot=True, cmap="rainbow")
```



The Year column isn't associated with the target Ratigns, thus will be excluded from the potential model input factors.

Furthermore, the Comments and the Views variables form multicollinearity with the Dislikes column, which is more related to the Rating, and should be removed as well.

The Budget and the Gross are interdependent, so the former is ought to be excluded as less related to the target.

```
[10] # removing not relevant for the analysis variables from the selected dataset
     data_num.drop(["Views", "Year", "Comments", "Budget"], axis=1, inplace=True)
     # show general stats of the relevant numerical feature columns
     data_num.describe().transpose()
```

	count	mean	std	min	25%	50%	75%	max
Ratings	231.0	6.441558e+00	9.887652e-01	3.1	5.8	6.5	7.100000e+00	8.7
Gross	231.0	6.806603e+07	8.890289e+07	2470.0	10300000.0	37400000.0	8.935000e+07	643000000.0
Dislikes	231.0	6.790519e+02	1.243929e+03	0.0	105.5	341.0	6.975000e+02	13960.0
Sentiment	231.0	2.809524e+00	6.996775e+00	-38.0	0.0	0.0	5.500000e+00	29.0
Genre	231.0	5.359307e+00	4.141611e+00	1.0	1.0	3.0	8.000000e+00	15.0
Sequel	231.0	1.359307e+00	9.672406e-01	1.0	1.0	1.0	1.000000e+00	7.0
Likes	231.0	1.273254e+04	2.882548e+04	1.0	1776.5	6096.0	1.524750e+04	370552.0
Aggregate Followers	231.0	3.038193e+06	4.499161e+06	1066.0	250000.0	1800000.0	3.038193e+06	31030000.0
Screens	231.0	2.209244e+03	1.431593e+03	2.0	563.5	2757.0	3.334000e+03	4324.0

The Sequel and Genre columns are the only containing categorical data that can be counted. The former is very unbalanced in the number of unique values, since more than 75% is filled with the same integer.

The Sentiment column representing a view of or attitude toward a movie ranges from negative to positive numbers, thus implies the overall data normalization.

```
[11] # counting unique values in the genre column
     data_num["Genre"].value_counts()
```

```
1     65
8     54
3     46
12    13
9     13
10    12
2     12
15    10
6      3
7      2
4      1
Name: Genre, dtype: int64
```

For some reason, this column has only 11 unique values, while the class indexes range from 1 to 15.

```
[12] # remapping genre column labels to the range from 0 to 10
     data_num['Genre'] = data_num['Genre'].map({value: i for i, value in
                                     enumerate(data_num['Genre'].unique())})
```

```
[13] # splitting the dataset to train (80%) and test (20%) subset dataframes
     train_data = data_num.sample(frac=0.8, random_state=1337)
     test_data = data_num.drop(train_data.index)

     # splitting the train and test datasets to X factors and y targets
     train_X, train_y = train_data.drop(target_col, axis=1), train_data[target_col].to_numpy()
     test_X, test_y = test_data.drop(target_col, axis=1), test_data[target_col].to_numpy()

     print(f"Original factor values:\t max {train_X.values.max()} - min {train_X.values.min()}")

     # defining a scaler to normalize training data
     scaler = MinMaxScaler()
     # defining feature columns set
     factor_cols = list(train_X.columns)
     # normalizing the data per-column, such that each numerical column of the dataset
     # which could be a potential predictor is scaled to the max absolute value of 1
     train_X = scaler.fit_transform(train_X)
     # applying the training data normalization parameters to the test dataset
     test_X = scaler.transform(test_X)

     print(f"Scaled factor values:\t max {round(train_X.max(), 2)} - min {train_X.min()}")

     print(f'Training data shape:\t{train_X.shape} - {train_y.shape}')
     print(f'Testing data shape:\t{test_X.shape} - {test_y.shape}')
```

```
Original factor values:  max 643000000.0 - min -38.0
Scaled factor values:    max 1.0 - min 0.0
Training data shape:    (185, 8) - (185,)
Testing data shape:     (46, 8) - (46,)
```

```
[14] # defining sequential regression model architecture
     def build_model():
       # creating a sequential model, which is a linear stack of layers
       model = keras.Sequential([
         # specifying the input shape based on the number of features in the training data
         layers.Dense(64, activation=tf.nn.relu, input_shape=[train_X.shape[1]]),
         # first two layers have 64 units each and using the ReLU activation function
         layers.Dense(64, activation=tf.nn.relu),
         # last layer returns a single continuous numerical value
         layers.Dense(1)
       ])

       # defining optimizer with a learning rate of 0.001 to minimize the training MSE loss
       optimizer = tf.keras.optimizers.RMSprop(0.001)
       # configuring the model for training by specifying the MSE loss function,
       # RMSprop optimizer, and two evaluation metrics - MAE and MSE
       model.compile(loss='mean_squared_error', optimizer=optimizer,
           metrics=['mean_absolute_error', 'mean_squared_error'])
       return model
```

```
[15] # initializing a new model instance
     model = build_model()
     model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                576

 dense_1 (Dense)             (None, 64)                4160

 dense_2 (Dense)             (None, 1)                 65

=================================================================
Total params: 4,801
Trainable params: 4,801
Non-trainable params: 0
_________________________________________________________________
```

The total number of layers is 3, input shape is (8,), the output shape is (1)

```
[16] # defining the dataloader batch size and number of training epochs
     batch_size = 32
     epochs = 1000
```

```
[17] # testing the model
     example_batch = train_X[:batch_size]
     example_predict = model.predict(example_batch)
     example_batch.shape, example_predict.shape
```

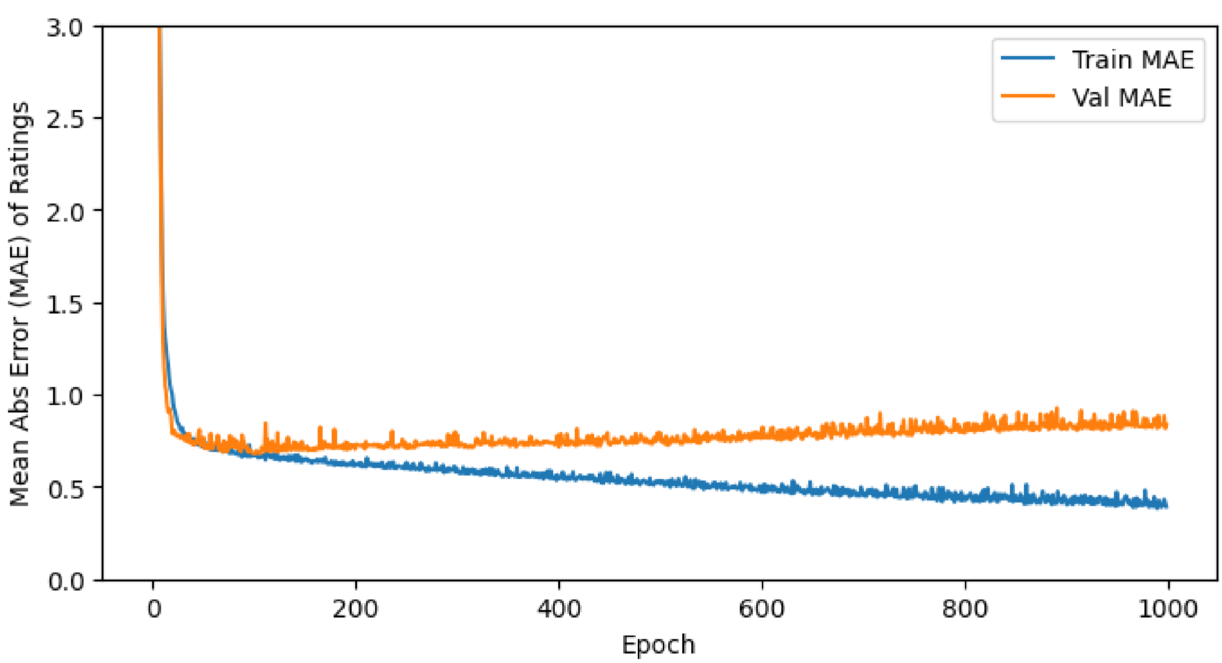
```
1/1 [==============================] - 1s 555ms/step
((32, 8), (32, 1))
```

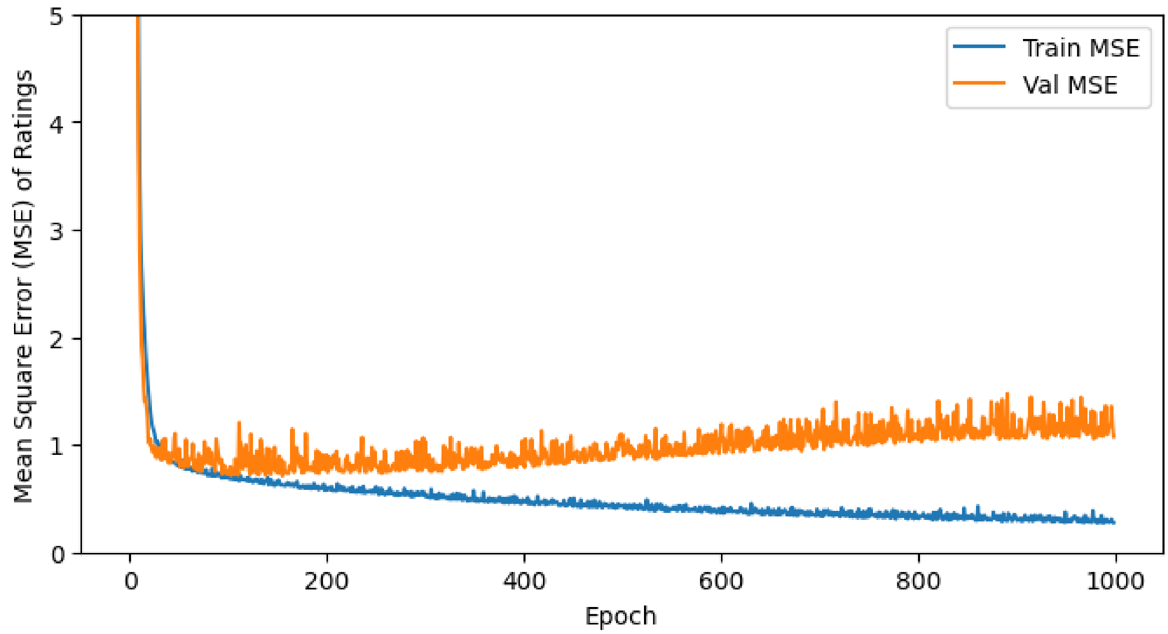
```
[18] # training the defined model to fit the training data which loaded in batches of
     # size 32 during 1000 epochs each finishing with the model accuracy evaluation on
     # the validation dataset (20%), while loss measures the average squared difference
     # between the predicted values and the true values in the batch
     model_train = model.fit(train_X, train_y, batch_size=batch_size,
                             epochs=epochs, verbose=0, validation_split=0.2)
     # forming pandas dataframe on the training stats data
     hist_data = pd.DataFrame(model_train.history)
     # adding a column of epoch numbers
     hist_data['epoch'] = model_train.epoch
     # show last 5 rows of the formed dataframe
     hist_data.tail()
```

loss	mean_absolute_error	mean_squared_error	val_loss	val_mean_absolute_error	val_mean_squared_error
0.288675	0.395360	0.288675	1.183462	0.836437	1.183462
0.283857	0.405342	0.283857	1.180987	0.835644	1.180987
0.309816	0.432301	0.309816	1.356930	0.884036	1.356930
0.288172	0.416017	0.288172	1.163503	0.815721	1.163503
0.276208	0.391852	0.276208	1.074537	0.837489	1.074537

```
[19] # function to draw accuracy graphs of the models training metrics
     def plot_history(model_train):
       # forming pandas dataframe on the training stats data
       hist = pd.DataFrame(model_train.history)
       # adding a column of epoch numbers
       hist['epoch'] = model_train.epoch

       # drawing graph lines of the recorded model performance metrics
       plt.figure(figsize=(8, 4))
       plt.xlabel('Epoch')
       plt.ylabel(f'Mean Abs Error (MAE) of {target_col}')
       plt.plot(hist['epoch'], hist['mean_absolute_error'], label='Train MAE')
       plt.plot(hist['epoch'], hist['val_mean_absolute_error'], label = 'Val MAE')
       plt.ylim([0, 3])
       plt.legend()

       plt.figure(figsize=(8, 4))
       plt.xlabel('Epoch')
       plt.ylabel(f'Mean Square Error (MSE) of {target_col}')
       plt.plot(hist['epoch'], hist['mean_squared_error'], label='Train MSE')
       plt.plot(hist['epoch'], hist['val_mean_squared_error'], label = 'Val MSE')
       plt.ylim([0, 5])
       plt.legend()
       plt.show()
```

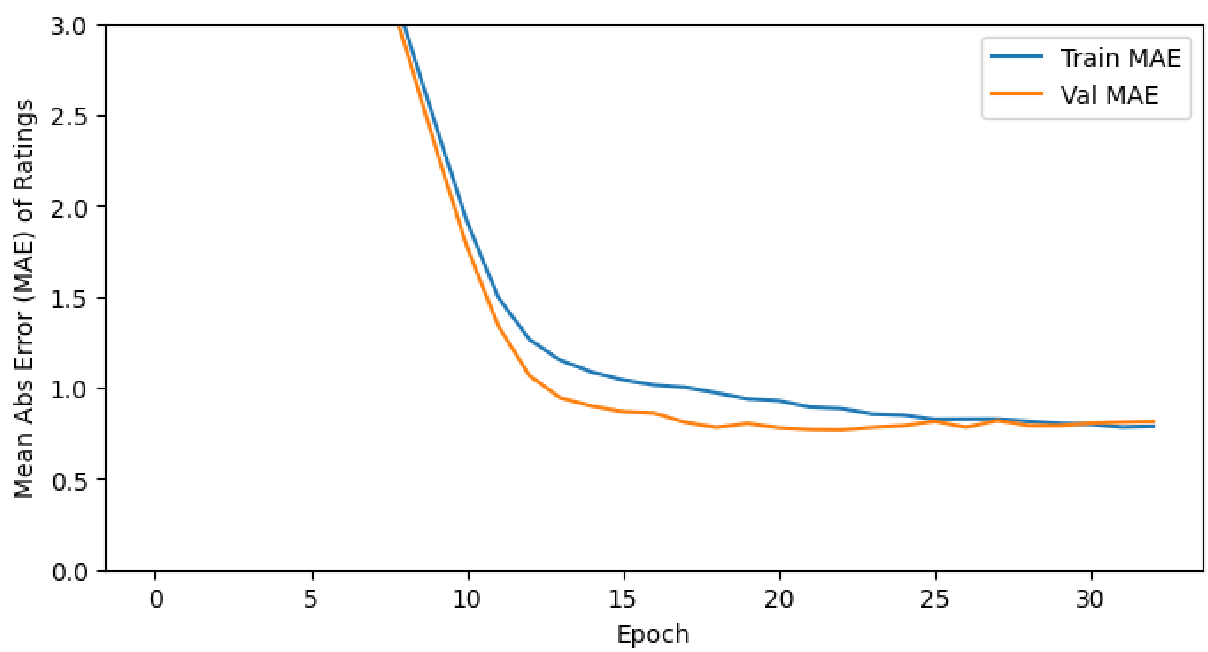
```
[20] # drawing performance metrics graphs for the trained model
     plot_history(model_train)
```

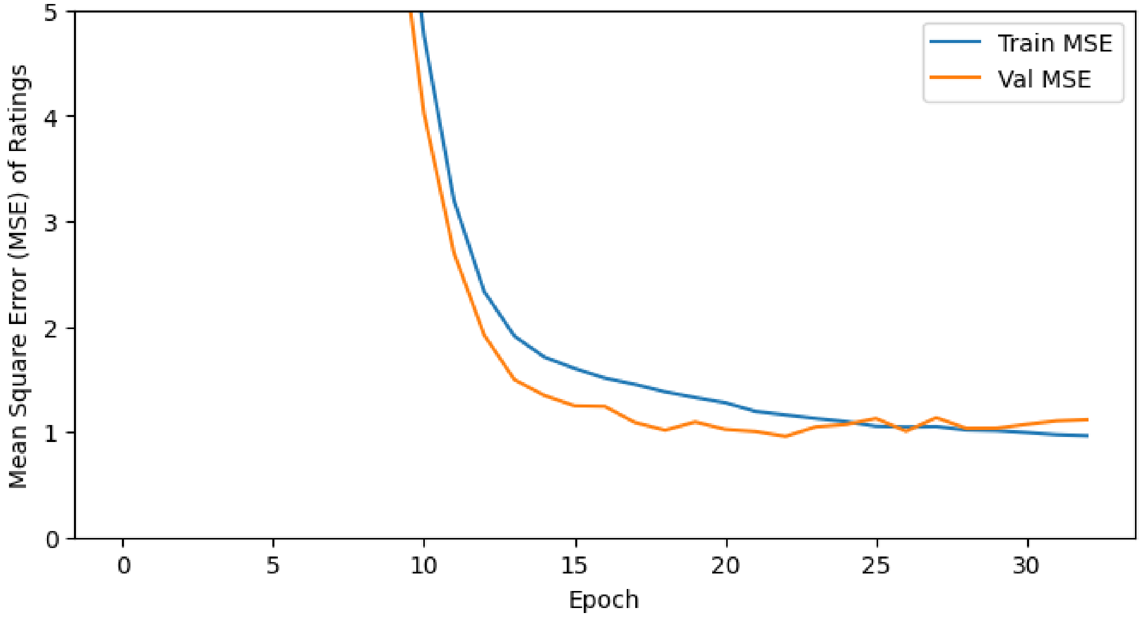


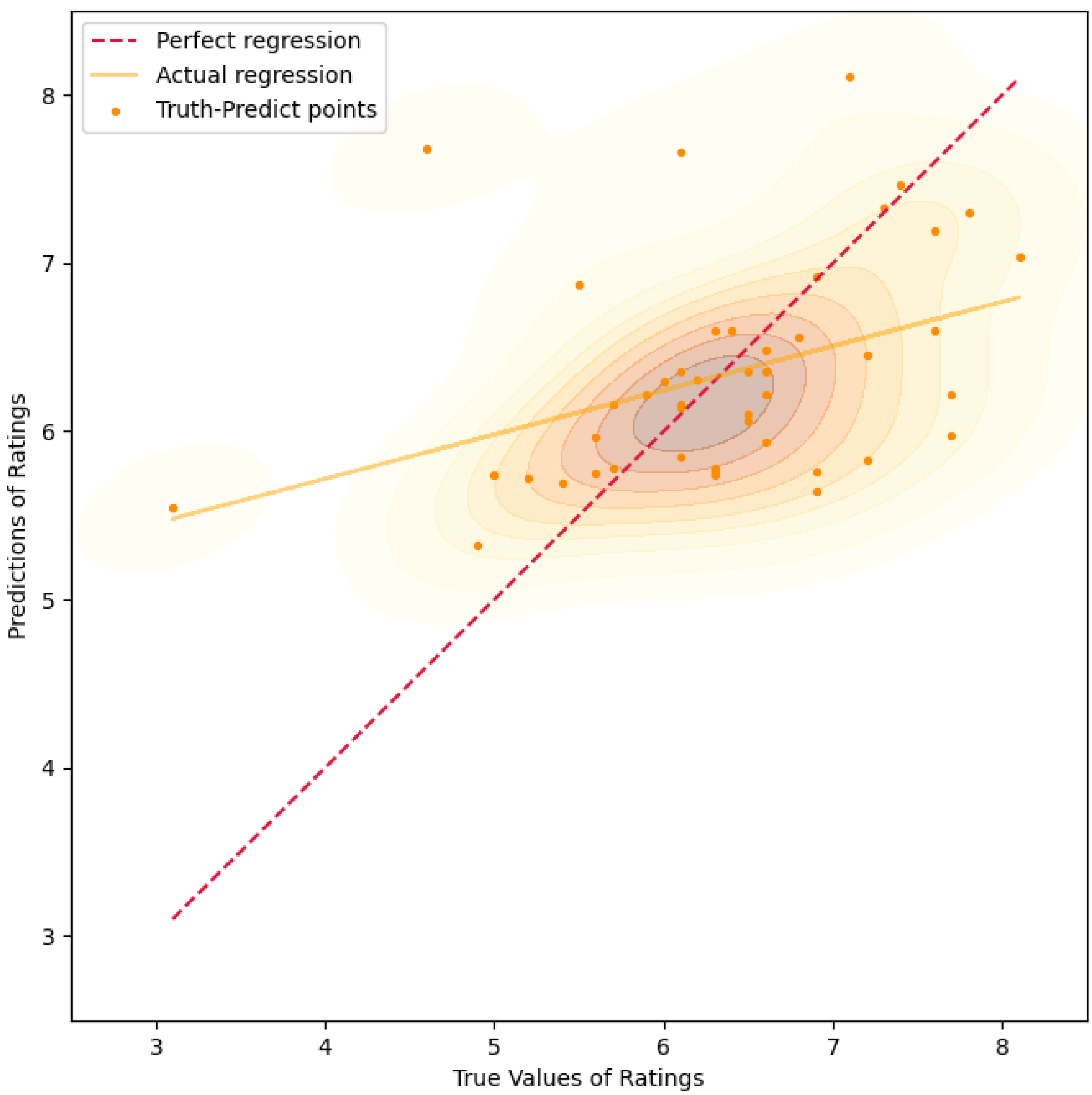


Validation MSE and MAE have been growing since epoch 50, the initial number of epochs was overestimated.

```
[21] # initializing new model instance of the same architecture
     model = build_model()
     # setting patience parameter as the amount of epochs to check for improvement
     early_stop = keras.callbacks.EarlyStopping(monitor='val_loss', patience=10)
     # training the defined model in the similar setting
     model_train = model.fit(train_X, train_y, batch_size=batch_size, epochs=epochs,
                             verbose=0, validation_split=0.2, callbacks=[early_stop])
     # drawing performance metrics graphs for the trained model
     plot_history(model_train)
```




Train MSE
Val MSE
Mean Square Error (MSE) of Ratings
Epoch
0
1
2
3
4
5
0
5
10
15
20
25
30


Perfect regression
Actual regression
Truth-Predict points
Predictions of Ratings
True Values of Ratings
3
4
5
6
7
8
3
4
5
6
7
8

After the 30th epoch the model was losing its generalization capability due to the data overfitting.

```
[22] # evaluating the model on the previously unseen test dataset
     test_eval = model.evaluate(test_X, test_y, verbose=0)
     print(f'Test loss:\t{test_eval[0]}')
     print(f'Test MAE:\t{test_eval[1]}')
     print(f'Test MSE:\t{test_eval[2]}')
```

```
Test loss:      0.8205345273017883
Test MAE:       0.6387553215026855
Test MSE:       0.8205345273017883
```

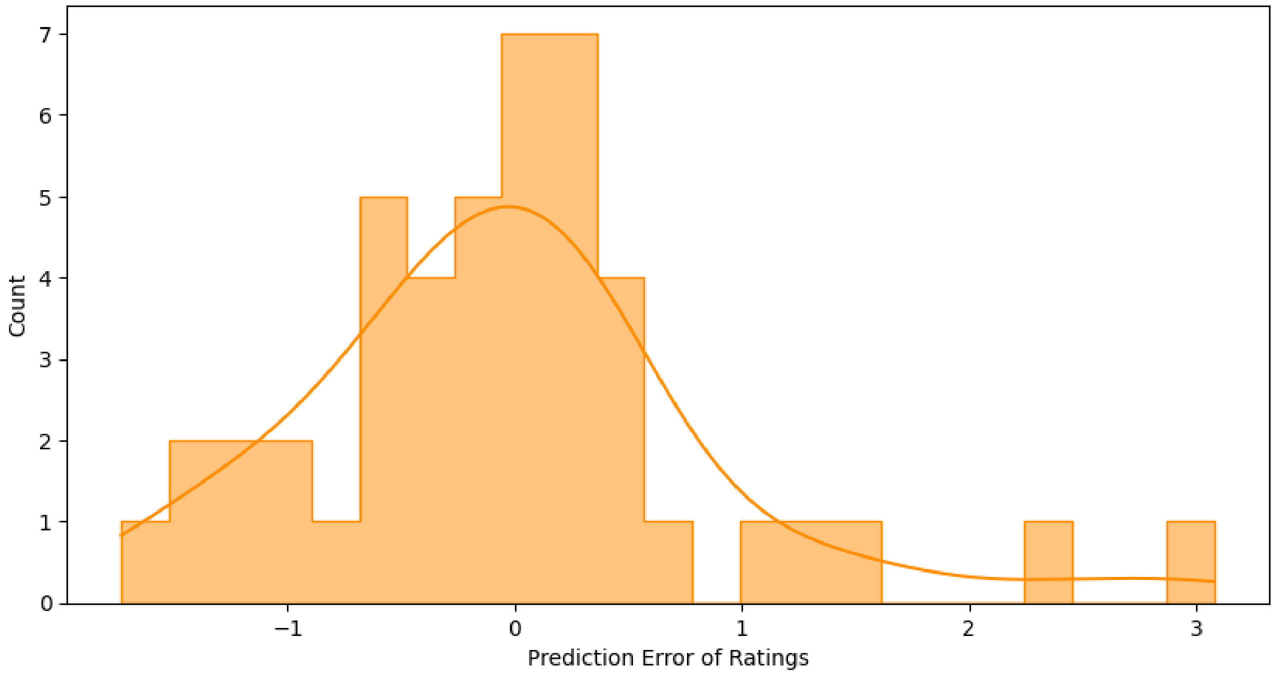
```
[23] # predicting the Rating for the test dataset inputs using the trained model
     test_predicts = model.predict(test_X).flatten()
     # calculating errors for the predicted values
     error = test_predicts - test_y

     test_predicts.shape, test_y.shape, error.shape
```

```
2/2 [==============================] - 0s 4ms/step
((46,), (46,), (46,))
```

```
[24] plt.figure(figsize=(8, 8))
     # drawing the perfect regression line in red
     steps = np.linspace(test_y.min(), test_y.max(), 100)
     plt.plot(steps, steps, linestyle='dashed', color="crimson", label="Perfect regression")
     # drawing the actual regression line in gold
     slope, intercept = np.polyfit(test_y, test_predicts, 1)
     plt.plot(test_y, slope * test_y + intercept, color='orange', alpha=0.5, label="Actual regression")
     # drawing data kernel density estimation lines
     sns.kdeplot(x=test_y, y=test_predicts, fill=True,
                 cmap=sns.color_palette("YlOrBr", as_cmap=True), alpha=0.3)
     # drawing scatter plot of the true and predicted values
     plt.scatter(test_y, test_predicts, color="darkorange", s=8, label="Truth-Predict points")
     plt.xlabel(f'True Values of {target_col}')
     plt.ylabel(f'Predictions of {target_col}')
     plt.ylim([2.5, 8.5])
     plt.xlim([2.5, 8.5])
     plt.legend()
     plt.show()
```

Considering the size of the initial dataset, the regression model demonstrates good enough results.

```
[25] # drawing histogram of prediction error distribution
     plt.figure(figsize=(10, 5))
     sns.histplot(error, kde=True, bins=23, color="darkorange", element="step")
     plt.xlabel(f'Prediction Error of {target_col}')
     plt.ylabel("Count")
     plt.show()
```



Вихідний код у jupyter notebook:

https://colab.research.google.com/drive/1ZnsfQ01bFYIMoiQH83dLmuPRjvZtID1x?usp=sharing

Висновки: було розглянуто основні методи мови Python, такі як TensorFlow, для побудови нейронних мереж з метою реалізації регресійних задач, з використанням структур даних та інструментів бібліотек Pandas та Sci-kit learn.