Problem Statement

You are a data scientist working for a school

You are asked to predict the GPA of the current students based on the following provided data:

0 StudentID int64
1 Age int64
2 Gender int64
3 Ethnicity int64
4 ParentalEducation int64
5 StudyTimeWeekly float64 6 Absences int64
7 Tutoring int64
8 ParentalSupport int64
9 Extracurricular int64
10 Sports int64
11 Music int64
12 Volunteering int64
13 GPA float64 14 GradeClass float64

The GPA is the Grade Point Average, typically ranges from 0.0 to 4.0 in most educational systems, with 4.0 representing an 'A' or excellent performance.

The minimum passing GPA can vary by institution, but it's often around 2.0. This usually corresponds to a 'C' grade, which is considered satisfactory.

You need to create a Deep Learning model capable to predict the GPA of a Student based on a set of provided features. The data provided represents 2,392 students.

In this excersice you will be requested to create a total of three models and select the most performant one.

1) Import Libraries

First let's import the following libraries, if there is any library that you need and is not in the list bellow feel free to include it

In [ ]:
```
import numpy as np
import pandas as pd
```

```
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten
from tensorflow.keras.regularizers import l2
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```
/Users/ricardosalinas/Library/Python/3.9/lib/python/site-packages/urllib3/__init__.py:35: NotOpenSSLWarning: urllib3 v2 only supports OpenSSL 1.1.1+, currently the 'ssl' module is compiled with 'LibreSSL 2.8.3'. See: https://github.com/urllib3/urllib3/issues/3020
  warnings.warn(
```

2) Load Data

- You will be provided with a cvs (comma separated value) file.
- You will need to add that file into a pandas dataframe, you can use the following code as reference
- The file will be available in canvas

In [ ]:

```
data = pd.read_csv("Student_performance_data _.csv")
data
```

Out[ ]:

	StudentID	Age	Gender	Ethnicity	ParentalEducation	StudyTimeWeekly	Abser
0	1001	17	1	0	2	19.833723	
1	1002	18	0	0	1	15.408756	
2	1003	15	0	2	3	4.210570	
3	1004	17	1	0	3	10.028829	
4	1005	17	1	0	2	4.672495	
...	...	...	...	...	...	...	
2387	3388	18	1	0	3	10.680555	
2388	3389	17	0	0	1	7.583217	
2389	3390	16	1	0	2	6.805500	
2390	3391	16	1	1	0	12.416653	
2391	3392	16	1	0	2	17.819907	

2392 rows × 15 columns

3) Review you data:

Make sure you review your data. Place special attention of null or empty values.

In [ ]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2392 entries, 0 to 2391
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   StudentID          2392 non-null   int64  
 1   Age                2392 non-null   int64  
 2   Gender             2392 non-null   int64  
 3   Ethnicity          2392 non-null   int64  
 4   ParentalEducation  2392 non-null   int64  
 5   StudyTimeWeekly    2392 non-null   float64
 6   Absences           2392 non-null   int64  
 7   Tutoring           2392 non-null   int64  
 8   ParentalSupport    2392 non-null   int64  
 9   Extracurricular    2392 non-null   int64  
 10  Sports             2392 non-null   int64  
 11  Music              2392 non-null   int64  
 12  Volunteering       2392 non-null   int64  
 13  GPA                2392 non-null   float64
 14  GradeClass         2392 non-null   float64
dtypes: float64(3), int64(12)
memory usage: 280.4 KB
```

4. Remove the columns not needed for Student performance prediction

- Choose only the columns you consider to be valuable for your model training.
- For example, StudentID might not be a good feature for your model, and thus should be removed from your main dataset, which other columns should also be removed?
- You can name that final dataset as 'dataset'

In [ ]:
```
# Your code here

dataset = data.drop(columns=["StudentID","Gender","Ethnicity"])
```

5. Check if the columns has any null values:

- Here you now have your final dataset to use in your model training.
- Before moving foward review your data check for any null or empty value that might be needed to be removed

In [ ]:
```
# Your code here

print(dataset.isnull().sum())
```

```
Age                  0
ParentalEducation    0
StudyTimeWeekly      0
Absences             0
Tutoring             0
ParentalSupport      0
Extracurricular      0
Sports               0
Music                0
Volunteering         0
GPA                  0
GradeClass           0
dtype: int64
```

6. Prepare your data for training and for testing set:

- First create a dataset named X, with all columns but GPA. These are the features
- Next create another dataset named y, with only GPA column. This is the label
- If you go to your Imports, you will see the following import: **'from sklearn.model_selection import train_test_split'**
- Use that *train_test_split* function to create: X_train, X_test, y_train and y_test respectively. Use X and y datasets as parameters. Other parameters to use are: Test Size = 0.2, Random State = 42.
- Standarize your features (X_train and X_test) by using the StandardScaler (investigate how to use fit_transform and transform functions). This will help the training process by dealing with normilized data.

Note: Your X_train shape should be around (1913, 10). This means the dataset has 10 columns which should be the input.

In [ ]:
```
# Your code here

X = dataset.drop(columns=['GPA'])
y = dataset['GPA']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

X_train = StandardScaler().fit_transform(X_train)

X_test = StandardScaler().fit_transform(X_test)
```

7. Define your Deep Neural Network.

- This will be a Sequential Neural Network.
- With a Dense input layer with 64 units, and input dimention of 10 and Relu as the activation function.
- A Dense hidden layer with 32 units, and Relu as the activation function.
- And a Dense output layer with 1 unit, do not define an activation function so it defaults to linear, suitable for regression tasks. e.g. Dense(1)

This last part of the output layer is super important, since we want to predict the GPA, this means that we want a regression and not a classification. Linear activation function is best for regression and Sigmoid is best for Binary Classification

In [ ]:
```
# Your code here

model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(32, activation='relu'),
    Dense(1)
])
```

8. Compile your Neural Network

- Choose Adam as the optimizer
- And MSE as the Loss function
- Also add the following metrics: Mean Absolute Error

In [ ]:
```
# Your code here

model.compile(
    optimizer='adam',
    loss='mse',
    metrics=['mae']
)
```

9. Fit (or train) your model

- Use the X_train and y_train datasets for the training
- Do 50 data iterations
- Choose the batch size = 10
- Also select a validation_split of 0.2
- Save the result of the fit function in a variable called 'history'

In [ ]:
```
# Your code here

history = model.fit(X_train, y_train, epochs=50, batch_size=10, validation_s
```

```
Epoch 1/50
153/153 [==============================] - 0s 1ms/step - loss: 0.7506 - mae:
0.5992 - val_loss: 0.1386 - val_mae: 0.2959
Epoch 2/50
153/153 [==============================] - 0s 669us/step - loss: 0.0993 - ma
e: 0.2498 - val_loss: 0.0803 - val_mae: 0.2273
Epoch 3/50
153/153 [==============================] - 0s 657us/step - loss: 0.0680 - ma
e: 0.2096 - val_loss: 0.0628 - val_mae: 0.1975
Epoch 4/50
153/153 [==============================] - 0s 643us/step - loss: 0.0548 - ma
e: 0.1891 - val_loss: 0.0581 - val_mae: 0.1933
Epoch 5/50
153/153 [==============================] - 0s 660us/step - loss: 0.0486 - ma
e: 0.1769 - val_loss: 0.0533 - val_mae: 0.1857
Epoch 6/50
153/153 [==============================] - 0s 695us/step - loss: 0.0442 - ma
e: 0.1684 - val_loss: 0.0492 - val_mae: 0.1786
Epoch 7/50
153/153 [==============================] - 0s 683us/step - loss: 0.0408 - ma
e: 0.1604 - val_loss: 0.0506 - val_mae: 0.1797
Epoch 8/50
153/153 [==============================] - 0s 704us/step - loss: 0.0395 - ma
e: 0.1581 - val_loss: 0.0498 - val_mae: 0.1781
Epoch 9/50
153/153 [==============================] - 0s 648us/step - loss: 0.0368 - ma
e: 0.1539 - val_loss: 0.0555 - val_mae: 0.1911
Epoch 10/50
153/153 [==============================] - 0s 652us/step - loss: 0.0360 - ma
e: 0.1512 - val_loss: 0.0491 - val_mae: 0.1781
Epoch 11/50
153/153 [==============================] - 0s 662us/step - loss: 0.0341 - ma
e: 0.1470 - val_loss: 0.0494 - val_mae: 0.1776
Epoch 12/50
153/153 [==============================] - 0s 658us/step - loss: 0.0334 - ma
e: 0.1450 - val_loss: 0.0534 - val_mae: 0.1838
Epoch 13/50
153/153 [==============================] - 0s 678us/step - loss: 0.0310 - ma
e: 0.1394 - val_loss: 0.0501 - val_mae: 0.1793
Epoch 14/50
153/153 [==============================] - 0s 695us/step - loss: 0.0312 - ma
e: 0.1410 - val_loss: 0.0490 - val_mae: 0.1787
Epoch 15/50
153/153 [==============================] - 0s 687us/step - loss: 0.0310 - ma
e: 0.1398 - val_loss: 0.0537 - val_mae: 0.1831
Epoch 16/50
```

```
153/153 [==============================] - 0s 701us/step - loss: 0.0294 - ma
e: 0.1361 - val_loss: 0.0489 - val_mae: 0.1718
Epoch 17/50
153/153 [==============================] - 0s 691us/step - loss: 0.0292 - ma
e: 0.1354 - val_loss: 0.0494 - val_mae: 0.1764
Epoch 18/50
153/153 [==============================] - 0s 648us/step - loss: 0.0291 - ma
e: 0.1354 - val_loss: 0.0477 - val_mae: 0.1722
Epoch 19/50
153/153 [==============================] - 0s 648us/step - loss: 0.0278 - ma
e: 0.1327 - val_loss: 0.0492 - val_mae: 0.1748
Epoch 20/50
153/153 [==============================] - 0s 637us/step - loss: 0.0266 - ma
e: 0.1293 - val_loss: 0.0499 - val_mae: 0.1759
Epoch 21/50
153/153 [==============================] - 0s 644us/step - loss: 0.0281 - ma
e: 0.1337 - val_loss: 0.0504 - val_mae: 0.1773
Epoch 22/50
153/153 [==============================] - 0s 640us/step - loss: 0.0271 - ma
e: 0.1303 - val_loss: 0.0480 - val_mae: 0.1726
Epoch 23/50
153/153 [==============================] - 0s 637us/step - loss: 0.0264 - ma
e: 0.1301 - val_loss: 0.0540 - val_mae: 0.1841
Epoch 24/50
153/153 [==============================] - 0s 674us/step - loss: 0.0256 - ma
e: 0.1270 - val_loss: 0.0504 - val_mae: 0.1766
Epoch 25/50
153/153 [==============================] - 0s 923us/step - loss: 0.0254 - ma
e: 0.1264 - val_loss: 0.0509 - val_mae: 0.1764
Epoch 26/50
153/153 [==============================] - 0s 703us/step - loss: 0.0244 - ma
e: 0.1235 - val_loss: 0.0518 - val_mae: 0.1779
Epoch 27/50
153/153 [==============================] - 0s 673us/step - loss: 0.0251 - ma
e: 0.1260 - val_loss: 0.0552 - val_mae: 0.1855
Epoch 28/50
153/153 [==============================] - 0s 651us/step - loss: 0.0240 - ma
e: 0.1214 - val_loss: 0.0513 - val_mae: 0.1795
Epoch 29/50
153/153 [==============================] - 0s 654us/step - loss: 0.0230 - ma
e: 0.1196 - val_loss: 0.0529 - val_mae: 0.1789
Epoch 30/50
153/153 [==============================] - 0s 668us/step - loss: 0.0235 - ma
e: 0.1213 - val_loss: 0.0539 - val_mae: 0.1815
Epoch 31/50
153/153 [==============================] - 0s 659us/step - loss: 0.0230 - ma
e: 0.1199 - val_loss: 0.0529 - val_mae: 0.1825
Epoch 32/50
153/153 [==============================] - 0s 678us/step - loss: 0.0225 - ma
e: 0.1186 - val_loss: 0.0508 - val_mae: 0.1760
```

```
Epoch 33/50
153/153 [==============================] - 0s 652us/step - loss: 0.0219 - ma
e: 0.1168 - val_loss: 0.0542 - val_mae: 0.1832
Epoch 34/50
153/153 [==============================] - 0s 681us/step - loss: 0.0218 - ma
e: 0.1172 - val_loss: 0.0558 - val_mae: 0.1848
Epoch 35/50
153/153 [==============================] - 0s 663us/step - loss: 0.0224 - ma
e: 0.1177 - val_loss: 0.0539 - val_mae: 0.1828
Epoch 36/50
153/153 [==============================] - 0s 654us/step - loss: 0.0222 - ma
e: 0.1176 - val_loss: 0.0542 - val_mae: 0.1843
Epoch 37/50
153/153 [==============================] - 0s 660us/step - loss: 0.0219 - ma
e: 0.1174 - val_loss: 0.0526 - val_mae: 0.1793
Epoch 38/50
153/153 [==============================] - 0s 714us/step - loss: 0.0211 - ma
e: 0.1145 - val_loss: 0.0549 - val_mae: 0.1836
Epoch 39/50
153/153 [==============================] - 0s 677us/step - loss: 0.0211 - ma
e: 0.1144 - val_loss: 0.0535 - val_mae: 0.1805
Epoch 40/50
153/153 [==============================] - 0s 660us/step - loss: 0.0209 - ma
e: 0.1146 - val_loss: 0.0547 - val_mae: 0.1836
Epoch 41/50
153/153 [==============================] - 0s 670us/step - loss: 0.0204 - ma
e: 0.1142 - val_loss: 0.0527 - val_mae: 0.1803
Epoch 42/50
153/153 [==============================] - 0s 677us/step - loss: 0.0199 - ma
e: 0.1112 - val_loss: 0.0576 - val_mae: 0.1874
Epoch 43/50
153/153 [==============================] - 0s 687us/step - loss: 0.0198 - ma
e: 0.1107 - val_loss: 0.0517 - val_mae: 0.1772
Epoch 44/50
153/153 [==============================] - 0s 676us/step - loss: 0.0193 - ma
e: 0.1103 - val_loss: 0.0516 - val_mae: 0.1777
Epoch 45/50
153/153 [==============================] - 0s 671us/step - loss: 0.0188 - ma
e: 0.1087 - val_loss: 0.0576 - val_mae: 0.1866
Epoch 46/50
153/153 [==============================] - 0s 660us/step - loss: 0.0188 - ma
e: 0.1069 - val_loss: 0.0515 - val_mae: 0.1776
Epoch 47/50
153/153 [==============================] - 0s 652us/step - loss: 0.0190 - ma
e: 0.1087 - val_loss: 0.0534 - val_mae: 0.1806
Epoch 48/50
153/153 [==============================] - 0s 648us/step - loss: 0.0194 - ma
e: 0.1102 - val_loss: 0.0524 - val_mae: 0.1787
Epoch 49/50
153/153 [==============================] - 0s 648us/step - loss: 0.0190 - ma
```

```
e: 0.1090 - val_loss: 0.0530 - val_mae: 0.1807
Epoch 50/50
153/153 [==============================] - 0s 646us/step - loss: 0.0177 - ma
e: 0.1052 - val_loss: 0.0534 - val_mae: 0.1797
```

10. View your history variable:

- Use Matplotlib.pyplot to show graphs of your model traning history
- In one graph:
  - Plot the Training Loss and the Validation Loss
  - X Label = Epochs
  - Y Label = Loss
  - Title = Training and Validation Loss over Epochs
- In a second graph:
  - Plot the Training MAE and the Validation MAE
  - X Label = Epochs
  - Y Label = Mean Absolute Error (MAE)
  - Title = Training and Validation MAE over Epochs

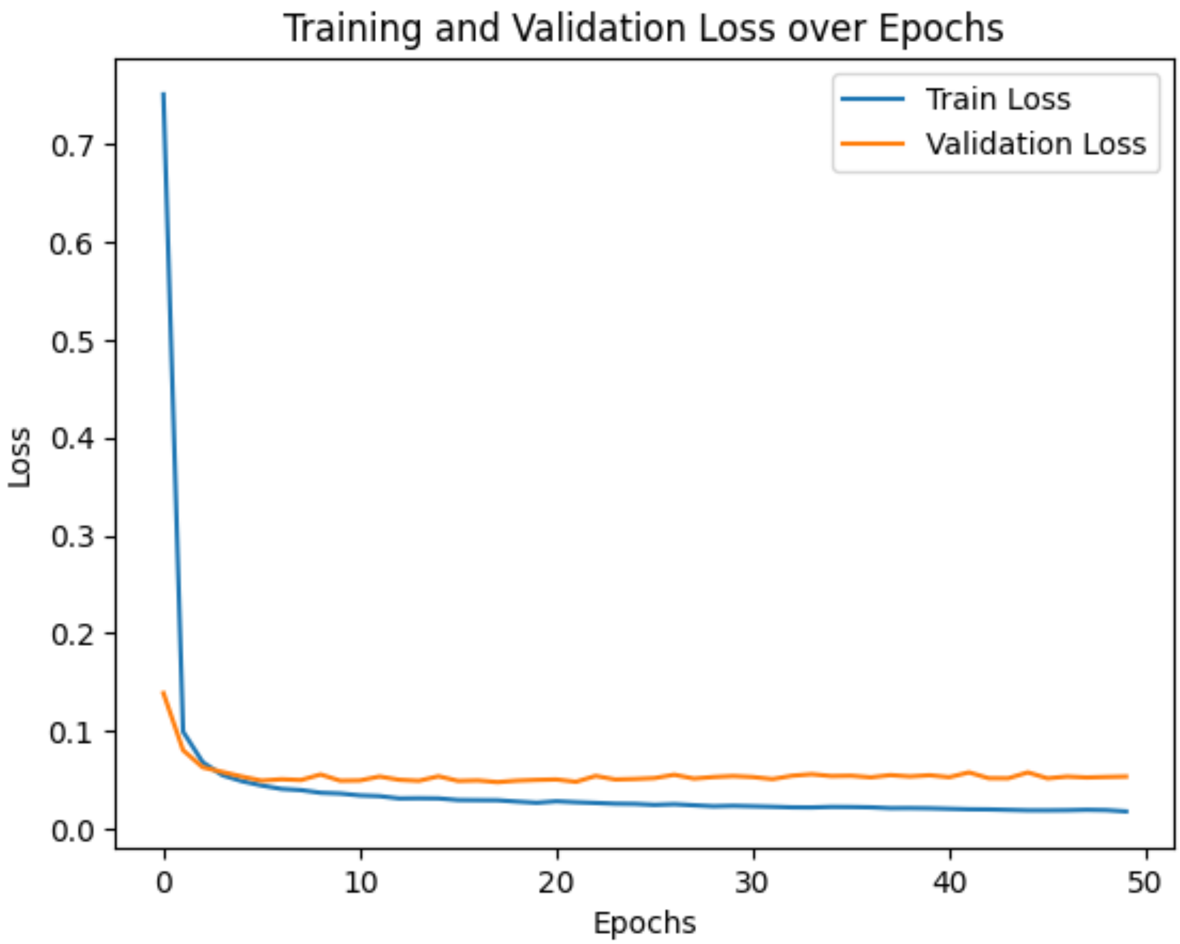
In [ ]:

```python
# Your code here

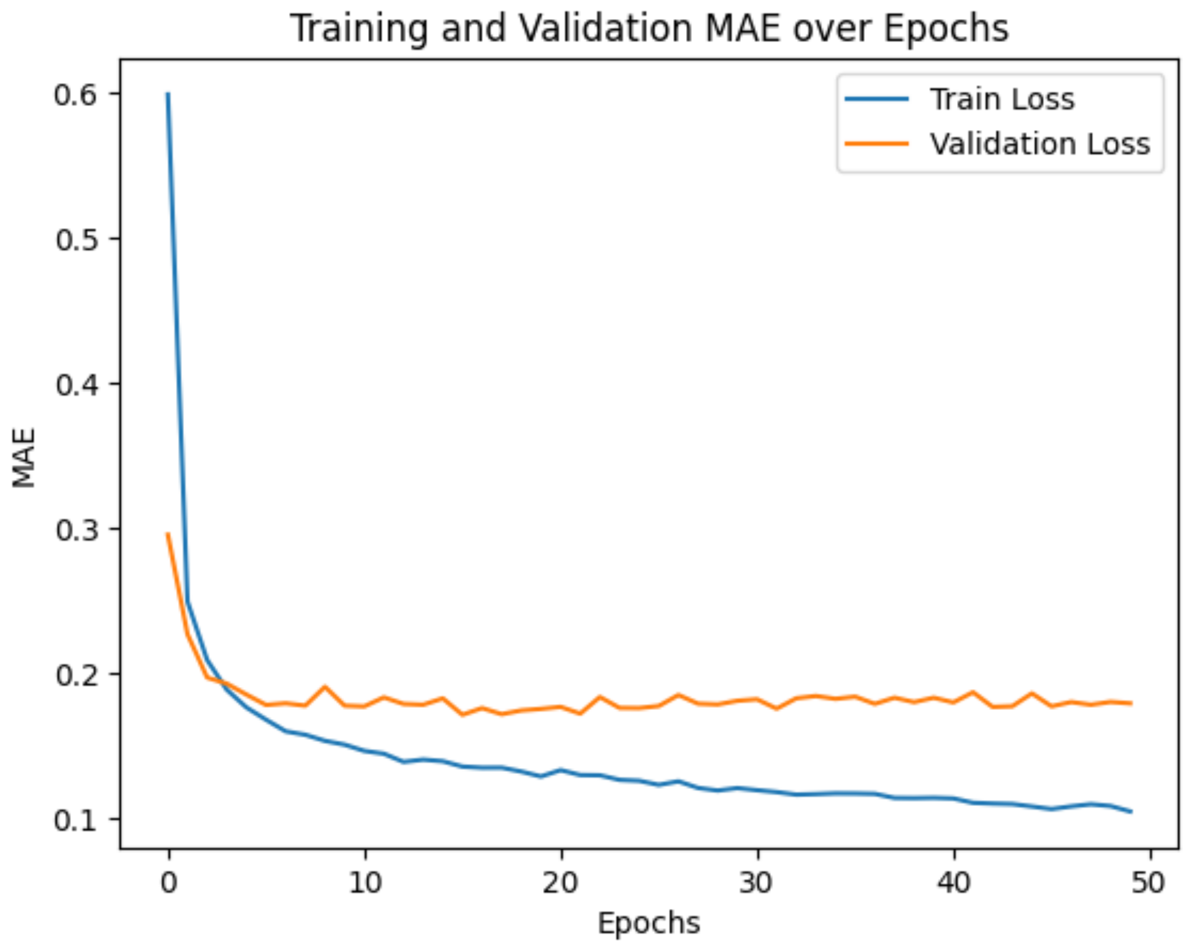
history_df = pd.DataFrame(history.history)



plt.plot(history_df['loss'], label='Train Loss')
plt.plot(history_df['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



In [ ]:
```
plt.plot(history_df['mae'], label='Train Loss')
plt.plot(history_df['val_mae'], label='Validation Loss')
plt.title('Training and Validation MAE over Epochs')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()
plt.show()
```



11. Evaluate your model:

- See the result of your loss function.
- What can you deduct from there?

In [ ]:
```
# Your code here
loss, mae = model.evaluate(X_test, y_test)
print("loss", loss)
print("mae", mae)
#print("mae", mae)
```

```
15/15 [==============================] - 0s 562us/step - loss: 0.0433 - mae: 0.1638
loss 0.043283745646476746
mae 0.16377253830432892
15/15 [==============================] - 0s 562us/step - loss: 0.0433 - mae: 0.1638
loss 0.043283745646476746
mae 0.16377253830432892
```

12. Use your model to make some predictions:

- Make predictions of your X_test dataset
- Print the each of the predictions and the actual value (which is in y_test)
- How good was your model?

In [ ]:
```
# Your code here

predictions = model.predict(X_test)

for i in range(len(y_test)):
    print(f'Prediction: {predictions[i,0]} Actual: {y_test.iloc[i]}')
#plt.scatter(X_test, y_test)
#plt.show()
```

```
15/15 [==============================] - 0s 471us/step
15/15 [==============================] - 0s 471us/step
Prediction: 1.4000802040100098 Actual: 1.4277243762746905
Prediction: 3.0010550022125244 Actual: 3.117354434785501
Prediction: 2.400912046432495 Actual: 2.037768574636005
Prediction: 3.6156165599823 Actual: 3.5485205508668662
Prediction: 0.5403100848197937 Actual: 0.2489771312307257
Prediction: 2.686645746231079 Actual: 2.627693905554347
Prediction: 1.739254117012024 Actual: 2.057378500596372
Prediction: 2.3083322048187256 Actual: 2.248337588471201
Prediction: 2.228379487991333 Actual: 2.1947065208246226
Prediction: 1.0038353204727173 Actual: 0.7581829737450007
Prediction: 2.584069013595581 Actual: 2.370893096932428
Prediction: 0.6945748925209045 Actual: 0.7664048694920337
Prediction: 2.9023499488830566 Actual: 2.952721567213245
Prediction: 2.6564018726348877 Actual: 2.3433313526833226
Prediction: 2.8949601650238037 Actual: 2.7718106588704914
Prediction: 0.0892275720834732 Actual: 0.2878673233291232
Prediction: 1.1058746576309204 Actual: 1.0182646498699195
Prediction: 1.50386381149292 Actual: 1.629355895809393
Prediction: 2.330312490463257 Actual: 2.0744387503601613
Prediction: 2.6139605045318604 Actual: 2.4238007516398317
Prediction: 1.900632619857788 Actual: 1.7562115530004156
Prediction: 1.6918708086013794 Actual: 1.5662885180613493
Prediction: 1.831261396408081 Actual: 1.7062124885863237
Prediction: 3.295605182647705 Actual: 3.161436270258364
Prediction: 1.6828227043151855 Actual: 1.733364046560005
Prediction: 0.6177818775177002 Actual: 0.8419632253726905
Prediction: 1.797547698020935 Actual: 1.3791671997209602
Prediction: 2.800363779067993 Actual: 3.0269833109614934
Prediction: 2.2032694816589355 Actual: 2.1919984196063775
Prediction: 2.10821533203125 Actual: 2.3157698749693236
Prediction: 2.128977060317993 Actual: 2.0681117849682034
Prediction: 0.7594614624977112 Actual: 0.869123386308555
```

```
Prediction: 2.89188551902771 Actual: 2.9000962392055474
Prediction: 3.189096212387085 Actual: 3.4685813491357274
Prediction: 1.5441371202468872 Actual: 1.5674124377048069
Prediction: 1.804646372795105 Actual: 1.7946671055341392
Prediction: 3.2236788272857666 Actual: 3.1813076022771107
Prediction: 3.14882755279541 Actual: 2.8973550040674096
Prediction: 3.340341806411743 Actual: 3.2448822032661777
Prediction: 0.5380337834358215 Actual: 0.3578088919508027
Prediction: 2.665935754776001 Actual: 2.6523548127186087
Prediction: 3.6443774700164795 Actual: 3.680961344427839
Prediction: 1.1410553455352783 Actual: 1.0363787383257312
Prediction: 2.0971786975860596 Actual: 2.017218038843316
Prediction: 0.8723639249801636 Actual: 0.9633750092514732
Prediction: 2.3914520740509033 Actual: 2.23946398594873
Prediction: 3.0131680965423584 Actual: 2.735960967147571
Prediction: 1.0181400775909424 Actual: 1.3619328272119078
Prediction: 3.0807864665985107 Actual: 2.70295861751592
Prediction: 1.394616961479187 Actual: 1.441918756451196
Prediction: 3.1718218326568604 Actual: 3.219531247903172
Prediction: 3.2861168384552 Actual: 3.3390943622003117
Prediction: 1.2191154956817627 Actual: 1.556218796080208
Prediction: 1.3071258068084717 Actual: 1.3423871779577343
Prediction: 1.7787258625030518 Actual: 1.756186167808898
Prediction: 3.396261215209961 Actual: 3.421837670026282
Prediction: 2.6753618717193604 Actual: 2.3169599744650875
Prediction: 3.502694606781006 Actual: 3.286585133610396
Prediction: 1.0128732919692993 Actual: 0.684651926072042
Prediction: 2.261592149734497 Actual: 2.1370681063433614
Prediction: 1.7227977514266968 Actual: 1.6884896091579062
Prediction: 1.9129093885421753 Actual: 2.1962173498725552
Prediction: 2.2269723415374756 Actual: 2.477790374289635
Prediction: 1.3949605226516724 Actual: 1.1979333311054492
Prediction: 0.9508963227272034 Actual: 0.9881530769380218
Prediction: 2.038811206817627 Actual: 1.8589248556209297
Prediction: 2.9707157611846924 Actual: 3.040729612939948
Prediction: 2.5121963024139404 Actual: 2.3741309720150148
Prediction: 1.24671471118927 Actual: 1.2212994205081906
Prediction: 3.5253591537475586 Actual: 3.2742334588098787
Prediction: 3.539909601211548 Actual: 3.5451594318003106
Prediction: 0.9504249691963196 Actual: 1.101939932271634
Prediction: 3.072364568710327 Actual: 2.968807133269986
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Prediction: 0.9929456114768982 Actual: 0.6768179731112823
Prediction: 2.4858736991882324 Actual: 2.504005287006646
Prediction: 2.0561680793762207 Actual: 2.122638529628868
Prediction: 2.7930819988250732 Actual: 2.977851918315743
Prediction: 2.649005651473999 Actual: 2.827614868021281
Prediction: 2.8178322315216064 Actual: 2.942198841728139
Prediction: 2.130113124847412 Actual: 2.309975847769393
Prediction: 2.692117929458618 Actual: 2.7778858935835875
Prediction: 2.5076992511749268 Actual: 2.524422658415435
Prediction: 2.0641279220581055 Actual: 2.135266354890094
Prediction: 2.4035286903381348 Actual: 2.224197461212005
Prediction: 3.2432916164398193 Actual: 3.2389317177358112
Prediction: 2.2456347942352295 Actual: 2.230253521333785
Prediction: 2.9380619525909424 Actual: 3.060805402033993
Prediction: 0.8122258186340332 Actual: 1.3635615499322744
Prediction: 3.4703996181488037 Actual: 3.603507572240497
Prediction: 2.0953359603881836 Actual: 2.1672829561454443
Prediction: 3.300828695297241 Actual: 3.3239029603291117
Prediction: 1.9219210147857666 Actual: 2.0165967745176614
Prediction: 1.427499771118164 Actual: 1.3620437691526197
Prediction: 2.081556797027588 Actual: 2.1156039687255843
Prediction: 2.332432270050049 Actual: 2.465306489467062
Prediction: 3.263410806655884 Actual: 3.060490750087925
Prediction: 1.8960357904434204 Actual: 1.9915084140251775
Prediction: 0.09602189064025879 Actual: 0.264924162952827
Prediction: 3.738065242767334 Actual: 3.64573804877044
Prediction: 2.3631370067596436 Actual: 2.5172289818586204
Prediction: 1.5380147695541382 Actual: 1.5487102111350304
Prediction: 1.530253291130066 Actual: 1.599593887728051
Prediction: 1.4105174541473389 Actual: 1.5538733401089513
Prediction: 2.4030098915100098 Actual: 2.5958890506964156
Prediction: 1.9613288640975952 Actual: 1.8790984603853385
Prediction: 1.3520911931991577 Actual: 1.5066627733506968
Prediction: 1.2324022054672241 Actual: 1.1048937876999445
Prediction: 0.7301213145256042 Actual: 0.3413935419913523
Prediction: 2.291994333267212 Actual: 2.4052675257641485
Prediction: 1.9401720762252808 Actual: 1.6848422066992197
Prediction: 3.077385902404785 Actual: 2.993502391205279
Prediction: 3.0838468074798584 Actual: 3.4154133242434344
Prediction: 1.422821044921875 Actual: 1.7097013783889978
```

```
Prediction: 1.7118290662765503 Actual: 1.5386892509239083
Prediction: 2.9401376247406006 Actual: 2.9213867570696292
Prediction: 2.5498921871185303 Actual: 2.605247445547851
Prediction: 2.2463531494140625 Actual: 2.4400060965135784
Prediction: 1.2421256303787231 Actual: 1.42899323811113
Prediction: 3.474597692489624 Actual: 3.3721260428259656
Prediction: 2.315807819366455 Actual: 2.1516179803357813
Prediction: 1.8027359247207642 Actual: 1.5950547587554351
Prediction: 1.4571672677993774 Actual: 1.4145556778225787
Prediction: 3.1337192058563232 Actual: 3.1288586460030157
Prediction: 2.8711798191070557 Actual: 2.553439811443938
Prediction: 3.008192300796509 Actual: 3.1296400506375512
Prediction: 2.917738676071167 Actual: 2.981992255406158
Prediction: 3.0215184688568115 Actual: 2.981786874282664
Prediction: 1.0264265537261963 Actual: 1.2010533026138683
Prediction: 2.5836188793182373 Actual: 2.7913861084723397
Prediction: 0.6336321234703064 Actual: 0.1530318116508149
Prediction: 0.7784184813499451 Actual: 0.6193509314675341
Prediction: 2.3020431995391846 Actual: 2.281345006080266
Prediction: 0.7822936177253723 Actual: 0.4937411351889655
Prediction: 2.7552835941314697 Actual: 2.966548034294946
Prediction: 1.8719309568405151 Actual: 1.989455195588546
Prediction: 3.7336056232452393 Actual: 3.5433159148930136
Prediction: 2.0202696323394775 Actual: 1.970600159244711
Prediction: 1.2422617673873901 Actual: 1.3440857175872982
Prediction: 0.7642878293991089 Actual: 1.027015599936749
Prediction: 0.6951931118965149 Actual: 0.4277633541749704
Prediction: 1.9011000394821167 Actual: 1.9746552454467765
Prediction: 0.9633151292800903 Actual: 1.242176324159397
Prediction: 0.6300084590911865 Actual: 0.384375395876116
Prediction: 0.6627135872840881 Actual: 0.4474828563605549
Prediction: 1.7283045053482056 Actual: 1.7290731666537256
Prediction: 2.105597496032715 Actual: 2.136399546240388
Prediction: 0.3375880718231201 Actual: 0.2109791787447653
Prediction: 0.18654508888721466 Actual: 0.33096690773874
Prediction: 2.8379323482513428 Actual: 2.8888916692724433
Prediction: 2.899617910385132 Actual: 3.2703738607764876
Prediction: 2.739579916000366 Actual: 2.500113299959695
Prediction: 1.2114230394363403 Actual: 1.212880751488374
Prediction: 1.8677767515182495 Actual: 2.009298479722319
Prediction: 1.180444359779358 Actual: 1.543837471085622
Prediction: 1.436176061630249 Actual: 1.4382049683676248
Prediction: 1.8456534147262573 Actual: 1.562359564441758
Prediction: 1.8410800695419312 Actual: 2.1749027962098797
Prediction: 2.4338796138763428 Actual: 2.3325403195354064
Prediction: 2.65360951423645 Actual: 2.777966932491008
Prediction: 0.9181432127952576 Actual: 0.863545351686935
```

13. Compete against this model:

- Create two more different models to compete with this model
- Here are a few ideas of things you can change:
  - During Dataset data engineering:
    - You can remove features that you think do not help in the training and prediction
    - Feature Scaling: Ensure all features are on a similar scale (as you already did with StandardScaler)
  - During Model Definition:
    - You can change the Model Architecture (change the type or number of layers or the number of units)
    - You can add dropout layers to prevent overfitting
  - During Model Compile:
    - You can try other optimizer when compiling your model, here some optimizer samples: Adam, RMSprop, or Adagrad.
    - Try another Loss Function
  - During Model Training:
    - Encrease the number of Epochs
    - Adjust the size of your batch
- Explain in a Markdown cell which changes are you implementing
- Show the comparison of your model versus the original model

Model 2:

- Changes:
  - Dataset Data Engineering
  - Model Definition
  - Model Compile
  - Model Training

In [ ]:
```
dataset2 = data.drop(columns=["StudentID","Gender","Ethnicity","Extracurricu

X2 = dataset2.drop(columns=['GPA'])
y2 = dataset2['GPA'].values

X2_train, X2_test, y2_train, y2_test = train_test_split(X2, y2, test_size=0.

scaler = StandardScaler()
X2_train = scaler.fit_transform(X2_train)
X2_test = scaler.transform(X2_test)

model2 = Sequential([
```

```
    Dense(64, activation='relu', input_dim=X2_train.shape[1]),
    Dense(32, activation='relu'),
    Dense(16, activation='relu'),
    Dense(1)
])

model2.compile(
    optimizer='adam',
    loss='mse',
    metrics=['mae']
)

history2 = model2.fit(X2_train, y2_train, epochs=75, batch_size=15, validati

loss2, mae2 = model2.evaluate(X2_test, y2_test)
print("loss", loss2)
print("mae", mae2)
```

```
Epoch 1/75
102/102 [==============================] - 0s 1ms/step - loss: 0.8757 - mae:
0.6788 - val_loss: 0.1819 - val_mae: 0.3429
Epoch 2/75
102/102 [==============================] - 0s 730us/step - loss: 0.1254 - ma
e: 0.2852 - val_loss: 0.1047 - val_mae: 0.2648
Epoch 3/75
102/102 [==============================] - 0s 697us/step - loss: 0.0875 - ma
e: 0.2384 - val_loss: 0.0925 - val_mae: 0.2437
Epoch 4/75
102/102 [==============================] - 0s 680us/step - loss: 0.0704 - ma
e: 0.2140 - val_loss: 0.0764 - val_mae: 0.2203
Epoch 5/75
102/102 [==============================] - 0s 683us/step - loss: 0.0606 - ma
e: 0.1979 - val_loss: 0.0716 - val_mae: 0.2140
Epoch 6/75
102/102 [==============================] - 0s 723us/step - loss: 0.0540 - ma
e: 0.1871 - val_loss: 0.0669 - val_mae: 0.2063
Epoch 7/75
102/102 [==============================] - 0s 749us/step - loss: 0.0499 - ma
e: 0.1783 - val_loss: 0.0612 - val_mae: 0.1962
Epoch 8/75
102/102 [==============================] - 0s 803us/step - loss: 0.0484 - ma
e: 0.1741 - val_loss: 0.0605 - val_mae: 0.1922
Epoch 9/75
102/102 [==============================] - 0s 775us/step - loss: 0.0449 - ma
e: 0.1684 - val_loss: 0.0647 - val_mae: 0.1985
Epoch 10/75
102/102 [==============================] - 0s 801us/step - loss: 0.0433 - ma
e: 0.1651 - val_loss: 0.0654 - val_mae: 0.2001
Epoch 11/75
102/102 [==============================] - 0s 990us/step - loss: 0.0430 - ma
```

```
e: 0.1632 - val_loss: 0.0634 - val_mae: 0.1975
Epoch 12/75
102/102 [==============================] - 0s 846us/step - loss: 0.0414 - ma
e: 0.1608 - val_loss: 0.0591 - val_mae: 0.1881
Epoch 13/75
102/102 [==============================] - 0s 774us/step - loss: 0.0414 - ma
e: 0.1598 - val_loss: 0.0631 - val_mae: 0.1947
Epoch 14/75
102/102 [==============================] - 0s 780us/step - loss: 0.0412 - ma
e: 0.1613 - val_loss: 0.0589 - val_mae: 0.1860
Epoch 15/75
102/102 [==============================] - 0s 766us/step - loss: 0.0397 - ma
e: 0.1566 - val_loss: 0.0569 - val_mae: 0.1834
Epoch 16/75
102/102 [==============================] - 0s 766us/step - loss: 0.0394 - ma
e: 0.1562 - val_loss: 0.0577 - val_mae: 0.1840
Epoch 17/75
102/102 [==============================] - 0s 753us/step - loss: 0.0382 - ma
e: 0.1538 - val_loss: 0.0610 - val_mae: 0.1891
Epoch 18/75
102/102 [==============================] - 0s 746us/step - loss: 0.0376 - ma
e: 0.1522 - val_loss: 0.0665 - val_mae: 0.2012
Epoch 19/75
102/102 [==============================] - 0s 739us/step - loss: 0.0372 - ma
e: 0.1507 - val_loss: 0.0624 - val_mae: 0.1916
Epoch 20/75
102/102 [==============================] - 0s 733us/step - loss: 0.0382 - ma
e: 0.1539 - val_loss: 0.0661 - val_mae: 0.1980
Epoch 21/75
102/102 [==============================] - 0s 735us/step - loss: 0.0361 - ma
e: 0.1482 - val_loss: 0.0651 - val_mae: 0.1942
Epoch 22/75
102/102 [==============================] - 0s 730us/step - loss: 0.0368 - ma
e: 0.1512 - val_loss: 0.0619 - val_mae: 0.1895
Epoch 23/75
102/102 [==============================] - 0s 779us/step - loss: 0.0342 - ma
e: 0.1444 - val_loss: 0.0648 - val_mae: 0.1947
Epoch 24/75
102/102 [==============================] - 0s 798us/step - loss: 0.0352 - ma
e: 0.1476 - val_loss: 0.0614 - val_mae: 0.1905
Epoch 25/75
102/102 [==============================] - 0s 797us/step - loss: 0.0352 - ma
e: 0.1465 - val_loss: 0.0604 - val_mae: 0.1885
Epoch 26/75
102/102 [==============================] - 0s 824us/step - loss: 0.0352 - ma
e: 0.1466 - val_loss: 0.0646 - val_mae: 0.1942
Epoch 27/75
102/102 [==============================] - 0s 735us/step - loss: 0.0357 - ma
e: 0.1460 - val_loss: 0.0579 - val_mae: 0.1849
Epoch 28/75
```

```
102/102 [==============================] - 0s 758us/step - loss: 0.0333 - ma
e: 0.1422 - val_loss: 0.0605 - val_mae: 0.1879
Epoch 29/75
102/102 [==============================] - 0s 764us/step - loss: 0.0368 - ma
e: 0.1519 - val_loss: 0.0601 - val_mae: 0.1857
Epoch 30/75
102/102 [==============================] - 0s 765us/step - loss: 0.0338 - ma
e: 0.1440 - val_loss: 0.0636 - val_mae: 0.1964
Epoch 31/75
102/102 [==============================] - 0s 747us/step - loss: 0.0342 - ma
e: 0.1448 - val_loss: 0.0623 - val_mae: 0.1922
Epoch 32/75
102/102 [==============================] - 0s 732us/step - loss: 0.0345 - ma
e: 0.1457 - val_loss: 0.0602 - val_mae: 0.1865
Epoch 33/75
102/102 [==============================] - 0s 734us/step - loss: 0.0327 - ma
e: 0.1410 - val_loss: 0.0589 - val_mae: 0.1846
Epoch 34/75
102/102 [==============================] - 0s 755us/step - loss: 0.0318 - ma
e: 0.1387 - val_loss: 0.0581 - val_mae: 0.1807
Epoch 35/75
102/102 [==============================] - 0s 760us/step - loss: 0.0317 - ma
e: 0.1387 - val_loss: 0.0621 - val_mae: 0.1890
Epoch 36/75
102/102 [==============================] - 0s 764us/step - loss: 0.0318 - ma
e: 0.1405 - val_loss: 0.0644 - val_mae: 0.1936
Epoch 37/75
102/102 [==============================] - 0s 738us/step - loss: 0.0307 - ma
e: 0.1375 - val_loss: 0.0590 - val_mae: 0.1837
Epoch 38/75
102/102 [==============================] - 0s 746us/step - loss: 0.0311 - ma
e: 0.1383 - val_loss: 0.0614 - val_mae: 0.1900
Epoch 39/75
102/102 [==============================] - 0s 745us/step - loss: 0.0314 - ma
e: 0.1383 - val_loss: 0.0641 - val_mae: 0.1937
Epoch 40/75
102/102 [==============================] - 0s 742us/step - loss: 0.0307 - ma
e: 0.1365 - val_loss: 0.0609 - val_mae: 0.1884
Epoch 41/75
102/102 [==============================] - 0s 753us/step - loss: 0.0305 - ma
e: 0.1367 - val_loss: 0.0652 - val_mae: 0.1968
Epoch 42/75
102/102 [==============================] - 0s 735us/step - loss: 0.0304 - ma
e: 0.1371 - val_loss: 0.0632 - val_mae: 0.1915
Epoch 43/75
102/102 [==============================] - 0s 721us/step - loss: 0.0294 - ma
e: 0.1345 - val_loss: 0.0612 - val_mae: 0.1914
Epoch 44/75
102/102 [==============================] - 0s 722us/step - loss: 0.0309 - ma
e: 0.1373 - val_loss: 0.0630 - val_mae: 0.1908
```

```
Epoch 45/75
102/102 [==============================] - 0s 966us/step - loss: 0.0287 - ma
e: 0.1336 - val_loss: 0.0665 - val_mae: 0.1968
Epoch 46/75
102/102 [==============================] - 0s 745us/step - loss: 0.0293 - ma
e: 0.1338 - val_loss: 0.0612 - val_mae: 0.1876
Epoch 47/75
102/102 [==============================] - 0s 725us/step - loss: 0.0302 - ma
e: 0.1371 - val_loss: 0.0623 - val_mae: 0.1912
Epoch 48/75
102/102 [==============================] - 0s 715us/step - loss: 0.0293 - ma
e: 0.1345 - val_loss: 0.0652 - val_mae: 0.1951
Epoch 49/75
102/102 [==============================] - 0s 718us/step - loss: 0.0280 - ma
e: 0.1297 - val_loss: 0.0617 - val_mae: 0.1895
Epoch 50/75
102/102 [==============================] - 0s 719us/step - loss: 0.0282 - ma
e: 0.1319 - val_loss: 0.0630 - val_mae: 0.1929
Epoch 51/75
102/102 [==============================] - 0s 712us/step - loss: 0.0281 - ma
e: 0.1304 - val_loss: 0.0666 - val_mae: 0.1963
Epoch 52/75
102/102 [==============================] - 0s 706us/step - loss: 0.0287 - ma
e: 0.1333 - val_loss: 0.0679 - val_mae: 0.2024
Epoch 53/75
102/102 [==============================] - 0s 718us/step - loss: 0.0272 - ma
e: 0.1286 - val_loss: 0.0641 - val_mae: 0.1933
Epoch 54/75
102/102 [==============================] - 0s 716us/step - loss: 0.0269 - ma
e: 0.1283 - val_loss: 0.0626 - val_mae: 0.1906
Epoch 55/75
102/102 [==============================] - 0s 709us/step - loss: 0.0254 - ma
e: 0.1243 - val_loss: 0.0623 - val_mae: 0.1917
Epoch 56/75
102/102 [==============================] - 0s 705us/step - loss: 0.0264 - ma
e: 0.1275 - val_loss: 0.0667 - val_mae: 0.2010
Epoch 57/75
102/102 [==============================] - 0s 738us/step - loss: 0.0276 - ma
e: 0.1297 - val_loss: 0.0615 - val_mae: 0.1896
Epoch 58/75
102/102 [==============================] - 0s 744us/step - loss: 0.0269 - ma
e: 0.1285 - val_loss: 0.0641 - val_mae: 0.1939
Epoch 59/75
102/102 [==============================] - 0s 750us/step - loss: 0.0256 - ma
e: 0.1244 - val_loss: 0.0619 - val_mae: 0.1887
Epoch 60/75
102/102 [==============================] - 0s 822us/step - loss: 0.0265 - ma
e: 0.1270 - val_loss: 0.0682 - val_mae: 0.1997
Epoch 61/75
102/102 [==============================] - 0s 729us/step - loss: 0.0252 - ma
```

```
e: 0.1243 - val_loss: 0.0677 - val_mae: 0.1989
Epoch 62/75
102/102 [==============================] - 0s 713us/step - loss: 0.0266 - ma
e: 0.1292 - val_loss: 0.0625 - val_mae: 0.1933
Epoch 63/75
102/102 [==============================] - 0s 717us/step - loss: 0.0271 - ma
e: 0.1298 - val_loss: 0.0737 - val_mae: 0.2080
Epoch 64/75
102/102 [==============================] - 0s 727us/step - loss: 0.0265 - ma
e: 0.1280 - val_loss: 0.0621 - val_mae: 0.1910
Epoch 65/75
102/102 [==============================] - 0s 745us/step - loss: 0.0260 - ma
e: 0.1248 - val_loss: 0.0679 - val_mae: 0.1994
Epoch 66/75
102/102 [==============================] - 0s 749us/step - loss: 0.0283 - ma
e: 0.1320 - val_loss: 0.0673 - val_mae: 0.2003
Epoch 67/75
102/102 [==============================] - 0s 747us/step - loss: 0.0256 - ma
e: 0.1259 - val_loss: 0.0664 - val_mae: 0.1983
Epoch 68/75
102/102 [==============================] - 0s 734us/step - loss: 0.0247 - ma
e: 0.1224 - val_loss: 0.0654 - val_mae: 0.1985
Epoch 69/75
102/102 [==============================] - 0s 726us/step - loss: 0.0253 - ma
e: 0.1241 - val_loss: 0.0690 - val_mae: 0.2022
Epoch 70/75
102/102 [==============================] - 0s 729us/step - loss: 0.0265 - ma
e: 0.1279 - val_loss: 0.0639 - val_mae: 0.1932
Epoch 71/75
102/102 [==============================] - 0s 740us/step - loss: 0.0247 - ma
e: 0.1226 - val_loss: 0.0656 - val_mae: 0.1969
Epoch 72/75
102/102 [==============================] - 0s 768us/step - loss: 0.0240 - ma
e: 0.1207 - val_loss: 0.0644 - val_mae: 0.1963
Epoch 73/75
102/102 [==============================] - 0s 715us/step - loss: 0.0244 - ma
e: 0.1228 - val_loss: 0.0694 - val_mae: 0.2030
Epoch 74/75
102/102 [==============================] - 0s 701us/step - loss: 0.0232 - ma
e: 0.1183 - val_loss: 0.0666 - val_mae: 0.1976
Epoch 75/75
102/102 [==============================] - 0s 719us/step - loss: 0.0243 - ma
e: 0.1208 - val_loss: 0.0631 - val_mae: 0.1929
15/15 [==============================] - 0s 467us/step - loss: 0.0653 - mae:
0.1958
loss 0.06530885398387909
mae 0.19576969742774963
```

Model 3:

- Changes:
  - Dataset Data Engineering
  - Model Definition
  - Model Compile
  - Model Training

In [ ]:
```
dataset3 = data.drop(columns=["StudentID","Gender","Ethnicity","Extracurricu

X3 = dataset3.drop(columns=['GPA'])
y3 = dataset3['GPA'].values

X3_train, X3_test, y3_train, y3_test = train_test_split(X3, y3, test_size=0.

scaler = StandardScaler()
X3_train = scaler.fit_transform(X3_train)
X3_test = scaler.transform(X3_test)

model3 = Sequential([
    Dense(64, activation='relu', input_dim=X3_train.shape[1]),
    Dropout(0.25),
    Dense(16, activation='relu'),
    Dense(1)
])

model3.compile(
    optimizer='adam',
    loss='mse',
    metrics=['mae']
)

history3 = model3.fit(X3_train, y3_train, epochs=75, batch_size=30, validati

loss3, mae3 = model3.evaluate(X3_test, y3_test)
print("loss", loss3)
print("mae", mae3)
```

```
Epoch 1/75
48/48 [==============================] - 0s 2ms/step - loss: 1.3832 - mae:
0.9442 - val_loss: 0.3172 - val_mae: 0.4512
Epoch 2/75
48/48 [==============================] - 0s 1ms/step - loss: 0.3254 - mae:
0.4482 - val_loss: 0.2077 - val_mae: 0.3688
Epoch 3/75
48/48 [==============================] - 0s 974us/step - loss: 0.2608 - mae:
0.4042 - val_loss: 0.1694 - val_mae: 0.3353
Epoch 4/75
48/48 [==============================] - 0s 943us/step - loss: 0.2366 - mae:
0.3866 - val_loss: 0.1449 - val_mae: 0.3085
```

```
Epoch 5/75
48/48 [==============================] - 0s 968us/step - loss: 0.2165 - mae:
0.3713 - val_loss: 0.1322 - val_mae: 0.2968
Epoch 6/75
48/48 [==============================] - 0s 963us/step - loss: 0.1984 - mae:
0.3505 - val_loss: 0.1187 - val_mae: 0.2817
Epoch 7/75
48/48 [==============================] - 0s 1ms/step - loss: 0.1877 - mae:
0.3433 - val_loss: 0.1078 - val_mae: 0.2671
Epoch 8/75
48/48 [==============================] - 0s 958us/step - loss: 0.1647 - mae:
0.3255 - val_loss: 0.1045 - val_mae: 0.2647
Epoch 9/75
48/48 [==============================] - 0s 913us/step - loss: 0.1599 - mae:
0.3201 - val_loss: 0.0982 - val_mae: 0.2559
Epoch 10/75
48/48 [==============================] - 0s 935us/step - loss: 0.1539 - mae:
0.3118 - val_loss: 0.0955 - val_mae: 0.2536
Epoch 11/75
48/48 [==============================] - 0s 901us/step - loss: 0.1556 - mae:
0.3148 - val_loss: 0.0875 - val_mae: 0.2419
Epoch 12/75
48/48 [==============================] - 0s 921us/step - loss: 0.1337 - mae:
0.2947 - val_loss: 0.0874 - val_mae: 0.2413
Epoch 13/75
48/48 [==============================] - 0s 921us/step - loss: 0.1297 - mae:
0.2875 - val_loss: 0.0813 - val_mae: 0.2322
Epoch 14/75
48/48 [==============================] - 0s 923us/step - loss: 0.1241 - mae:
0.2776 - val_loss: 0.0800 - val_mae: 0.2306
Epoch 15/75
48/48 [==============================] - 0s 918us/step - loss: 0.1073 - mae:
0.2596 - val_loss: 0.0779 - val_mae: 0.2276
Epoch 16/75
48/48 [==============================] - 0s 914us/step - loss: 0.1093 - mae:
0.2618 - val_loss: 0.0750 - val_mae: 0.2234
Epoch 17/75
48/48 [==============================] - 0s 921us/step - loss: 0.1083 - mae:
0.2596 - val_loss: 0.0764 - val_mae: 0.2262
Epoch 18/75
48/48 [==============================] - 0s 911us/step - loss: 0.1026 - mae:
0.2569 - val_loss: 0.0699 - val_mae: 0.2160
Epoch 19/75
48/48 [==============================] - 0s 914us/step - loss: 0.0988 - mae:
0.2507 - val_loss: 0.0682 - val_mae: 0.2125
Epoch 20/75
48/48 [==============================] - 0s 901us/step - loss: 0.0950 - mae:
0.2458 - val_loss: 0.0728 - val_mae: 0.2201
Epoch 21/75
48/48 [==============================] - 0s 910us/step - loss: 0.0907 - mae:
```

```
0.2410 - val_loss: 0.0649 - val_mae: 0.2047
Epoch 22/75
48/48 [==============================] - 0s 898us/step - loss: 0.0897 - mae:
0.2357 - val_loss: 0.0636 - val_mae: 0.2046
Epoch 23/75
48/48 [==============================] - 0s 922us/step - loss: 0.0847 - mae:
0.2313 - val_loss: 0.0598 - val_mae: 0.1969
Epoch 24/75
48/48 [==============================] - 0s 911us/step - loss: 0.0851 - mae:
0.2315 - val_loss: 0.0606 - val_mae: 0.2002
Epoch 25/75
48/48 [==============================] - 0s 907us/step - loss: 0.0826 - mae:
0.2272 - val_loss: 0.0590 - val_mae: 0.1940
Epoch 26/75
48/48 [==============================] - 0s 911us/step - loss: 0.0787 - mae:
0.2222 - val_loss: 0.0576 - val_mae: 0.1919
Epoch 27/75
48/48 [==============================] - 0s 910us/step - loss: 0.0784 - mae:
0.2228 - val_loss: 0.0569 - val_mae: 0.1911
Epoch 28/75
48/48 [==============================] - 0s 963us/step - loss: 0.0736 - mae:
0.2152 - val_loss: 0.0601 - val_mae: 0.1990
Epoch 29/75
48/48 [==============================] - 0s 918us/step - loss: 0.0731 - mae:
0.2159 - val_loss: 0.0587 - val_mae: 0.1948
Epoch 30/75
48/48 [==============================] - 0s 887us/step - loss: 0.0702 - mae:
0.2116 - val_loss: 0.0613 - val_mae: 0.2001
Epoch 31/75
48/48 [==============================] - 0s 888us/step - loss: 0.0707 - mae:
0.2111 - val_loss: 0.0583 - val_mae: 0.1944
Epoch 32/75
48/48 [==============================] - 0s 883us/step - loss: 0.0695 - mae:
0.2087 - val_loss: 0.0546 - val_mae: 0.1851
Epoch 33/75
48/48 [==============================] - 0s 908us/step - loss: 0.0684 - mae:
0.2076 - val_loss: 0.0551 - val_mae: 0.1887
Epoch 34/75
48/48 [==============================] - 0s 894us/step - loss: 0.0706 - mae:
0.2130 - val_loss: 0.0554 - val_mae: 0.1859
Epoch 35/75
48/48 [==============================] - 0s 893us/step - loss: 0.0678 - mae:
0.2092 - val_loss: 0.0633 - val_mae: 0.2038
Epoch 36/75
48/48 [==============================] - 0s 896us/step - loss: 0.0637 - mae:
0.2013 - val_loss: 0.0537 - val_mae: 0.1831
Epoch 37/75
48/48 [==============================] - 0s 902us/step - loss: 0.0660 - mae:
0.2060 - val_loss: 0.0503 - val_mae: 0.1765
Epoch 38/75
```

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48/48 [==============================] - 0s 891us/step - loss: 0.0627 - mae:
0.1999 - val_loss: 0.0520 - val_mae: 0.1807
Epoch 39/75
48/48 [==============================] - 0s 885us/step - loss: 0.0655 - mae:
0.2013 - val_loss: 0.0506 - val_mae: 0.1759
Epoch 40/75
48/48 [==============================] - 0s 895us/step - loss: 0.0682 - mae:
0.2035 - val_loss: 0.0513 - val_mae: 0.1798
Epoch 41/75
48/48 [==============================] - 0s 896us/step - loss: 0.0647 - mae:
0.2012 - val_loss: 0.0521 - val_mae: 0.1795
Epoch 42/75
48/48 [==============================] - 0s 912us/step - loss: 0.0642 - mae:
0.1988 - val_loss: 0.0513 - val_mae: 0.1783
Epoch 43/75
48/48 [==============================] - 0s 912us/step - loss: 0.0625 - mae:
0.1978 - val_loss: 0.0514 - val_mae: 0.1796
Epoch 44/75
48/48 [==============================] - 0s 893us/step - loss: 0.0627 - mae:
0.1974 - val_loss: 0.0575 - val_mae: 0.1925
Epoch 45/75
48/48 [==============================] - 0s 895us/step - loss: 0.0616 - mae:
0.1967 - val_loss: 0.0506 - val_mae: 0.1750
Epoch 46/75
48/48 [==============================] - 0s 915us/step - loss: 0.0603 - mae:
0.1920 - val_loss: 0.0493 - val_mae: 0.1734
Epoch 47/75
48/48 [==============================] - 0s 910us/step - loss: 0.0633 - mae:
0.1972 - val_loss: 0.0519 - val_mae: 0.1792
Epoch 48/75
48/48 [==============================] - 0s 904us/step - loss: 0.0583 - mae:
0.1895 - val_loss: 0.0536 - val_mae: 0.1832
Epoch 49/75
48/48 [==============================] - 0s 911us/step - loss: 0.0582 - mae:
0.1888 - val_loss: 0.0527 - val_mae: 0.1813
Epoch 50/75
48/48 [==============================] - 0s 879us/step - loss: 0.0620 - mae:
0.1958 - val_loss: 0.0497 - val_mae: 0.1748
Epoch 51/75
48/48 [==============================] - 0s 902us/step - loss: 0.0559 - mae:
0.1840 - val_loss: 0.0496 - val_mae: 0.1752
Epoch 52/75
48/48 [==============================] - 0s 921us/step - loss: 0.0587 - mae:
0.1884 - val_loss: 0.0498 - val_mae: 0.1739
Epoch 53/75
48/48 [==============================] - 0s 899us/step - loss: 0.0549 - mae:
0.1823 - val_loss: 0.0508 - val_mae: 0.1762
Epoch 54/75
48/48 [==============================] - 0s 904us/step - loss: 0.0548 - mae:
0.1828 - val_loss: 0.0486 - val_mae: 0.1709
```

```
Epoch 55/75
48/48 [==============================] - 0s 907us/step - loss: 0.0582 - mae:
0.1918 - val_loss: 0.0485 - val_mae: 0.1721
Epoch 56/75
48/48 [==============================] - 0s 901us/step - loss: 0.0556 - mae:
0.1863 - val_loss: 0.0523 - val_mae: 0.1793
Epoch 57/75
48/48 [==============================] - 0s 905us/step - loss: 0.0530 - mae:
0.1800 - val_loss: 0.0503 - val_mae: 0.1734
Epoch 58/75
48/48 [==============================] - 0s 912us/step - loss: 0.0571 - mae:
0.1883 - val_loss: 0.0520 - val_mae: 0.1785
Epoch 59/75
48/48 [==============================] - 0s 891us/step - loss: 0.0558 - mae:
0.1839 - val_loss: 0.0488 - val_mae: 0.1702
Epoch 60/75
48/48 [==============================] - 0s 917us/step - loss: 0.0544 - mae:
0.1825 - val_loss: 0.0531 - val_mae: 0.1817
Epoch 61/75
48/48 [==============================] - 0s 911us/step - loss: 0.0580 - mae:
0.1869 - val_loss: 0.0521 - val_mae: 0.1792
Epoch 62/75
48/48 [==============================] - 0s 914us/step - loss: 0.0565 - mae:
0.1863 - val_loss: 0.0479 - val_mae: 0.1693
Epoch 63/75
48/48 [==============================] - 0s 909us/step - loss: 0.0550 - mae:
0.1826 - val_loss: 0.0486 - val_mae: 0.1719
Epoch 64/75
48/48 [==============================] - 0s 905us/step - loss: 0.0531 - mae:
0.1805 - val_loss: 0.0480 - val_mae: 0.1701
Epoch 65/75
48/48 [==============================] - 0s 912us/step - loss: 0.0535 - mae:
0.1818 - val_loss: 0.0499 - val_mae: 0.1744
Epoch 66/75
48/48 [==============================] - 0s 918us/step - loss: 0.0559 - mae:
0.1838 - val_loss: 0.0501 - val_mae: 0.1763
Epoch 67/75
48/48 [==============================] - 0s 900us/step - loss: 0.0547 - mae:
0.1852 - val_loss: 0.0489 - val_mae: 0.1724
Epoch 68/75
48/48 [==============================] - 0s 898us/step - loss: 0.0541 - mae:
0.1826 - val_loss: 0.0480 - val_mae: 0.1701
Epoch 69/75
48/48 [==============================] - 0s 925us/step - loss: 0.0526 - mae:
0.1771 - val_loss: 0.0563 - val_mae: 0.1886
Epoch 70/75
48/48 [==============================] - 0s 893us/step - loss: 0.0570 - mae:
0.1866 - val_loss: 0.0548 - val_mae: 0.1829
Epoch 71/75
48/48 [==============================] - 0s 918us/step - loss: 0.0541 - mae:
```

```
0.1803 - val_loss: 0.0476 - val_mae: 0.1687
Epoch 72/75
48/48 [==============================] - 0s 905us/step - loss: 0.0537 - mae:
0.1831 - val_loss: 0.0529 - val_mae: 0.1811
Epoch 73/75
48/48 [==============================] - 0s 904us/step - loss: 0.0534 - mae:
0.1805 - val_loss: 0.0523 - val_mae: 0.1791
Epoch 74/75
48/48 [==============================] - 0s 899us/step - loss: 0.0509 - mae:
0.1746 - val_loss: 0.0473 - val_mae: 0.1676
Epoch 75/75
48/48 [==============================] - 0s 909us/step - loss: 0.0547 - mae:
0.1822 - val_loss: 0.0552 - val_mae: 0.1853
15/15 [==============================] - 0s 469us/step - loss: 0.0567 - mae:
0.1866
loss 0.05666549131274223
mae 0.1865626573562622
```

In [ ]:

```
X_test_sample = X_test[:5]
y_test_sample = y_test[:5]

X_test_sample2 = X2_test[:5]
X_test_sample3 = X3_test[:5]


predictions_model = model.predict(X_test_sample)
predictions_model2 = model2.predict(X_test_sample2)
predictions_model3 = model3.predict(X_test_sample3)


resultados = pd.DataFrame({
    'y_test_real': y_test_sample,
    'Predicción Model1': predictions_model.flatten(),
    'Predicción Model2': predictions_model2.flatten(),
    'Predicción Model3': predictions_model3.flatten()
})

print(resultados)
```

```
1/1 [==============================] - 0s 11ms/step
1/1 [==============================] - 0s 11ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 26ms/step
      y_test_real  Predicción Model1  Predicción Model2  Predicción Model3
1004     1.427724           1.400080           1.480011           1.270870
196      3.117354           3.001055           3.132015           2.921779
2342     2.037769           2.400912           1.858790           2.141569
1708     3.548521           3.615617           3.623375           3.444747
435      0.248977           0.540310           0.453103           0.438697
```