homework-task2

October 13, 2023

1 Report

For our machine learning task I chose to use linear regression. For this I chose to use the dataset https://archive.ics.uci.edu/dataset/320/student+performance. In this Dataset I used the 'student-mat.csv'. I made a machine learning model I tried to predict the final score using the information about the school, sex, age, address, studytime, absences, first score and second score of the student. I also made some visualisations using this csv file so that you know what the data is about and what information is in the file. I did not have a lit of problems during the first part of this exercise (The linear regression part). Everything went pretty smoothly and I did not have look anything up.

As additional ML techniques I chose 'Gradient Boosting Regressor' and 'Support Vector Machine (SVM) Regression' wich I explain later in the document. For these techniques I did not have to search a lot to create the code. It was pretty simple to find how I had to implement the techniques.

The streamlit part was a bit more difficult to make. Instead of just using one model I had to train 3 different models when you start the application. For this I had to think a bit about the best way to do this. The rest was not that difficult to do. Exept for getting the data inside the cloud environment (I used chatGPT for this see below).

For my Ai tool I used chatGPT to get my csv file inside the streamlit cloud environment. The template I used was 'how can I put a csv file from my github in a streamlit cloud app without putting it in myself' and the reaction I got was 'GITHUB_RAW_URL = "https://raw.githubusercontent.com/yourusername/yourrepository/main/yourfile.csv" response = requests.get(GITHUB_RAW_URL)'. You can also find this in my streamlit code to load the data.

Streamlit: https://kieran-cornelissen-homework-task2.streamlit.app/

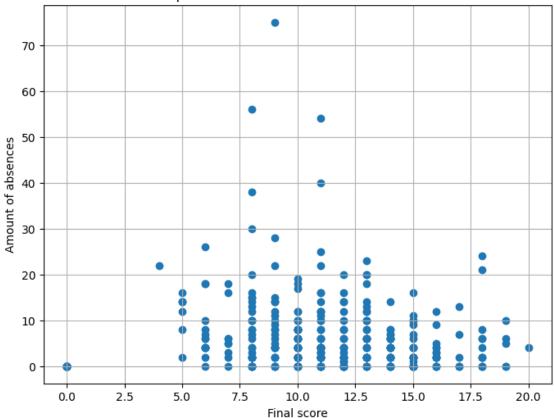
2 Linear Regression

```
[19]: # import The necessery libraries and the csv file we are going to use
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import category_encoders as ce
```

```
student_df = pd.read_csv('./data/student-mat.csv',delimiter=';')
 [2]: # Show us what the data looks like
      print(student df.shape)
      print(student_df.describe())
     (395, 33)
                                                   traveltime
                                                                 studytime
                                Medu
                                             Fedu
                                                                               failures
                    age
     count
             395.000000
                          395.000000
                                      395.000000
                                                   395.000000
                                                                395.000000
                                                                             395.000000
                                         2.521519
                                                      1.448101
                                                                  2.035443
                                                                               0.334177
     mean
              16.696203
                            2.749367
                            1.094735
                                         1.088201
                                                      0.697505
                                                                  0.839240
                                                                               0.743651
     std
               1.276043
                                         0.000000
                                                      1.000000
     min
              15.000000
                            0.000000
                                                                  1.000000
                                                                               0.000000
     25%
                                         2.000000
              16.000000
                            2.000000
                                                      1.000000
                                                                  1.000000
                                                                               0.000000
     50%
              17.000000
                            3.000000
                                         2.000000
                                                      1.000000
                                                                  2.000000
                                                                               0.000000
     75%
              18.000000
                            4.000000
                                         3.000000
                                                      2.000000
                                                                  2.000000
                                                                               0.000000
              22.000000
                            4.000000
                                         4.000000
                                                      4.000000
                                                                  4.000000
                                                                                3.000000
     max
                 famrel
                            freetime
                                                          Dalc
                                                                       Walc
                                                                                  health
                                            goout
             395.000000
                          395.000000
                                      395.000000
                                                   395.000000
                                                                395.000000
                                                                             395.000000
     count
               3.944304
                            3.235443
                                         3.108861
                                                      1.481013
                                                                  2.291139
                                                                               3.554430
     mean
     std
               0.896659
                            0.998862
                                         1.113278
                                                      0.890741
                                                                  1.287897
                                                                                1.390303
     min
               1.000000
                            1.000000
                                         1.000000
                                                      1.000000
                                                                  1.000000
                                                                               1.000000
     25%
                            3.000000
                                         2.000000
                                                      1.000000
               4.000000
                                                                  1.000000
                                                                               3.000000
     50%
               4.000000
                            3.000000
                                         3.000000
                                                      1.000000
                                                                  2.000000
                                                                               4.000000
               5.000000
     75%
                            4.000000
                                         4.000000
                                                      2.000000
                                                                  3.000000
                                                                               5.000000
                                         5.000000
                                                      5.000000
               5.000000
                            5.000000
                                                                  5.000000
                                                                               5.000000
     max
                                                            G3
               absences
                                  G1
                                               G2
                                                    395.000000
             395.000000
                          395.000000
                                       395.000000
     count
     mean
               5.708861
                           10.908861
                                        10.713924
                                                     10.415190
     std
               8.003096
                            3.319195
                                         3.761505
                                                      4.581443
               0.000000
                            3.000000
                                         0.000000
                                                      0.00000
     min
     25%
               0.000000
                            8.000000
                                         9.000000
                                                      8.000000
     50%
                           11.000000
                                        11.000000
                                                     11.000000
               4.000000
     75%
               8.000000
                           13.000000
                                        13.000000
                                                     14.000000
                                        19.000000
     max
              75.000000
                           19.000000
                                                     20.000000
[13]: # Show all the distinct values of the final score
      student_df['G3'].value_counts()
[13]: 10
            56
      11
            47
      0
            38
      15
            33
      8
            32
      13
            31
      12
            31
```

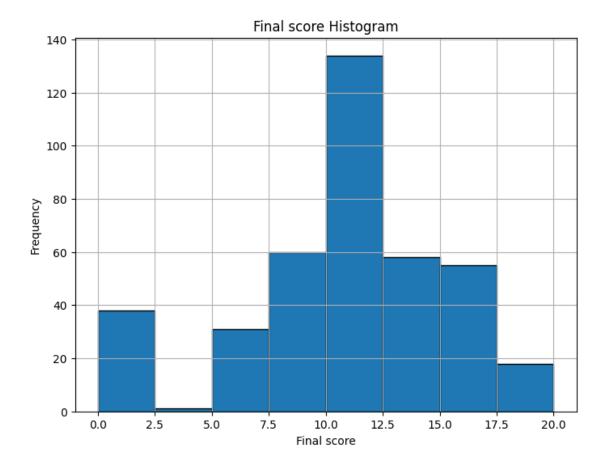
```
9
            28
      14
            27
      16
            16
      6
            15
      18
            12
      7
             9
      5
             7
      17
             6
      19
             5
      20
             1
      4
             1
     Name: G3, dtype: int64
[20]: # Plot a figure of the relation between the final score and the amount of \Box
      ⇔absences
     plt.figure(figsize=(8, 6))
      plt.scatter(student_df['G3'], student_df['absences'], alpha=1.0)
      plt.title('Relationship between final score and amount of absences')
      plt.xlabel('Final score')
      plt.ylabel('Amount of absences')
      plt.grid(True)
      plt.show()
```





```
[21]: # Show the frequentie of all the different values fo the final scores
    plt.figure(figsize=(8, 6))
    plt.hist(student_df['G3'], bins=8, edgecolor='k')
    plt.title('Final score Histogram')
    plt.xlabel('Final score')
    plt.ylabel('Frequency')
    plt.grid(True)

plt.show()
```



```
print('Dependent:',y_train)
     independent:
                      school sex age address studytime absences G1 G2
     64
              1
                       15
                                           2
                                                       10
                   1
                                1
                                                    0
                                                           10
     55
                                           2
                                                            9
              1
                       16
                                                    8
                                                        8
                   1
                                1
     343
              1
                   1
                       17
                                1
                                           2
                                                    0
                                                        9
                                                            8
                                           3
     219
              1
                       17
                                1
                                                    4
                                                        9
                                                           10
              2
                                           3
                                                       13 13
     366
                   2
                       18
                                1
                                                    0
     . .
     323
              1
                   1
                       17
                                1
                                           3
                                                    1
                                                       12 14
     192
              1
                   2
                       17
                                1
                                           2
                                                    12
                                                        7
                                                            8
                                                    0 13 14
     117
              1
                   2
                       16
                                1
                                           1
                                1
     47
              1
                   2
                       16
                                           4
                                                    4
                                                       19
                                                           19
     172
              1
                       17
                                1
                                           2
                                                    0
                                                       13 11
     [316 rows x 8 columns]
                     school sex age address studytime absences G1 G2
     independent:
     64
            GP
                 F
                     15
                             U
                                        2
                                                 0
                                                    10
                                                        10
     55
            GΡ
                 F
                     16
                             U
                                        2
                                                  8
                                                     8
                                                         9
                 F
            GP
                                        2
                                                     9
                                                         8
     343
                     17
                             U
                                                 0
     219
            GP
                F
                             U
                                        3
                                                 4
                                                     9
                                                       10
                     17
     366
            MS
                 Μ
                     18
                             U
                                        3
                                                 0
                                                    13
                                                       13
     . .
                                        •••
     323
            GP
                 F
                     17
                             U
                                        3
                                                 1 12 14
     192
            GP
                     17
                             U
                                        2
                                                 12
                                                     7
                 Μ
     117
            GP
                     16
                             U
                                        1
                                                 0 13 14
                 Μ
     47
            GP
                 М
                     16
                             U
                                        4
                                                 4
                                                    19 19
                                        2
     172
            GP
                             U
                 Μ
                     17
                                                 0 13 11
     [316 rows x 8 columns]
[66]: # We use linear regression from the library we installed earlier and fit our
      →model using the X and Y from the training set we created above
     model = LinearRegression()
     model.fit(X_train, y_train)
     # Then we print the intercept and coefficient af our data
     print('Intercept', model.intercept_)
     print('Coefficient', model.coef_)
     Intercept 2.4932231592204737
     0.05853222
       0.11524352 0.98535703]
```

[65]: # Print the data in the X training set and the Y trainingset

print('independent:',X_train)

```
[67]: # Here we reshape the array of coefficients so that we can print it together.
      ⇔with the titel they belong to
     coefficients = model.coef_.reshape(8,-1)
     variables = np.array([['school', 'sex', 'age', 'address', 'studytime', __
      coeff = pd.DataFrame(coefficients, variables)
     print(coeff)
                          0
     (school,)
                  0.610556
     (sex,)
                  0.207563
     (age,)
                  -0.306919
     (address,)
                  -0.086966
     (studytime,) 0.053397
     (absences,)
                  0.058532
     (G1,)
                  0.115244
     (G2,)
                   0.985357
[68]: # Then we try to predict the Y (Final score) values by using the values of the
      \hookrightarrow X testset
     y_pred = model.predict(X_test).round().astype(int)
[69]: # Now we print the actual values of the Y test set and the predicted values so
      ⇔we can compare them
     result_df = pd.DataFrame({'Actual': y_test[:25], 'Predicted': y_pred[:25]})
     print(result_df)
          Actual Predicted
              14
                         14
     329
     318
              10
                         10
                         9
     317
              9
     65
              15
                         15
     59
              16
                         16
     287
              12
                         12
     212
              14
                         13
                         11
     60
              11
     394
              9
                         8
     324
              15
                         15
     375
                         7
              10
     74
              11
                         15
     76
              10
                         12
     106
              8
                         8
     215
              15
                         15
              14
                         14
     12
```

132	12	13
264	0	9
268	10	9
167	16	15
168	0	6
150	0	4
90	8	6
171	16	15
282	12	11

C:\Users\kiera\AppData\Local\Temp\ipykernel_1928\1425366346.py:1: FutureWarning: The behavior of `series[i:j]` with an integer-dtype index is deprecated. In a future version, this will be treated as *label-based* indexing, consistent with e.g. `series[i]` lookups. To retain the old behavior, use `series.iloc[i:j]`. To get the future behavior, use `series.loc[i:j]`.

result_df = pd.DataFrame({'Actual': y_test[:25], 'Predicted': y_pred[:25]})

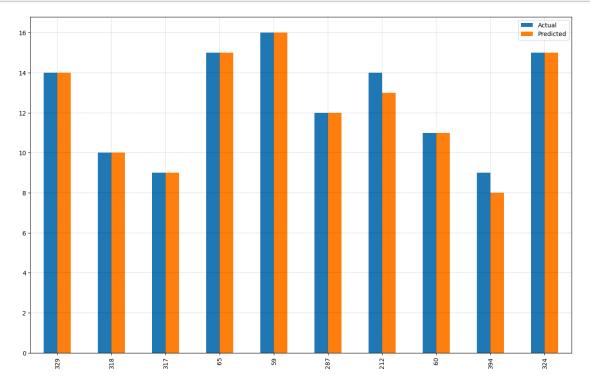
```
[70]: # Here I make a bar chart to compare the first 10 values of the actual Y and the predicted Y values

result10_df = result_df.head(10)

result10_df.plot(kind='bar', figsize=(16,10))

plt.grid(linestyle=':', linewidth='0.25', color='black')

plt.show()
```



```
[71]: # Here we calculate the R<sup>2</sup> score. This is how 'good' our model is (the closengeto 1 the better the prediction)

from sklearn.metrics import r2_score

r_squared = r2_score(y_test, y_pred)

print("R<sup>2</sup> Value:", r_squared)
```

R2 Value: 0.7912383408254058

```
[83]: # Here we can give in the features of a student and our model will try to \Box
      ⇔predict what this students final score will be
      # First we make all the input fields for all of our values
      new student features = {}
      school = input('What school are you attending (For Gabriel Pereira insert GP, __

¬for Mousinho da Silveira insert MS): ').upper().strip()

      sex = input('What sex are you (For female insert F, for male insert M): ').
      →upper().strip()
      age = input('How old are you: ')
      address = input('Do you live in an urban (insert U) or a rural (insert R)_{\sqcup}
       →neighboorhood: ').upper().strip()
      studytime = input('How long do you study: ')
      studytime = int(studytime)
      absences = input('How manny times were you absent: ')
      G1 = input('What was your first score: ')
      G2 = input('What was your second score: ')
      # Because I made it so you have to give a string for the school, sex and
      →address I have an if that sets this to the numbers given to the
       ⇔corresponding values
      # We also add all of these features to the new_student_features so we can use_
      ⇔this to make our prediction
      if school == 'GP':
          new_student_features['school'] = 1
      elif school == 'MS':
          new student features['school'] = 2
      if sex == 'F':
         new_student_features['sex'] = 1
      elif sex == 'M':
          new_student_features['sex'] = 2
      new_student_features['age'] = age
      if address == 'U':
          new_student_features['address'] = 1
      elif address == 'R':
          new_student_features['address'] = 2
```

```
if studytime < 2:
    new_student_features['studytime'] = 1
elif studytime < 5:</pre>
    new_student_features['studytime'] = 2
elif studytime < 10:</pre>
    new student features['studytime'] = 3
else:
    new student features['studytime'] = 4
new student features['absences'] = absences
new student features['G1'] = G1
new student features['G2'] = G2
# We turn the new student features into a pandas dataframe and then use the
 →model.predict function on this dataframe. And at the end we print the
 ⇔predicted value
new_student_df = pd.DataFrame([new_student_features])
predicted_G3 = model.predict(new_student_df).round().astype(int)
print("Predicted final score:", predicted G3[0])
```

Predicted final score: 11.821164120613783

3 Gradient Boosting Regressor

Gradient Boosting Regressor makes predictions by combining the predictions of multiple weak regression models (usually decision trees) in a stage-wise manner. These are the steps it uses:

Initialization: The algorithm starts with an initial prediction, often set to the mean of the target variable (in the case of regression). This initial prediction represents the "residuals" at the beginning.

Fitting Weak Models (Decision Trees): Gradient Boosting Regressor fits a weak regression model (typically shallow decision trees) to the dataset. These models are typically called "base learners" or "weak learners." The base learner is trained to predict the residuals (the difference between the actual target values and the current predictions).

Updating Predictions: The predictions from the current base learner are added to the previous predictions to improve the model's accuracy. The contribution of each base learner is controlled by a learning rate (often a small value like 0.1). This step updates the predictions incrementally.

Calculating Residuals: The algorithm calculates the residuals, which are the differences between the true target values and the current predictions. The subsequent base learner is then trained to predict these residuals.

Iterative Process: Steps 2 to 4 are repeated for a specified number of boosting stages (controlled by the n estimators hyperparameter). In each stage, a new base learner is trained to predict the

residuals from the previous stage.

Final Prediction: The final prediction is obtained by summing up the predictions from all base learners. The learning rate also controls the contribution of each base learner to the final prediction.

4 Code

```
[1]: # Here we do all of our imports
     from sklearn.ensemble import GradientBoostingRegressor
     from sklearn.model_selection import train_test_split
     from sklearn.metrics import mean_squared_error
     import pandas as pd
     # We grab the csv file and read it in as a pandas dataframe
     student df = pd.read_csv('./data/student-mat.csv',delimiter=';')
     # Then we declare all the variables we want to use to make a prediction
     features = ['school', 'sex', 'age', 'address', 'studytime', 'absences', 'G1', __
      \# We use the data frame to make our X and Y values
     X = student df[features]
     y = student_df['G3']
     # Here we turn the values of school, sex and address into numbers
     X = pd.get_dummies(X, columns=['school', 'sex', 'address'], drop_first=True)
     # We split our model 80% training setand 20% testing set
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,_
      →random_state=0)
     # Then we use the GradientBoostingRegressor from our earlier imports and we fit,
      →the model using Gradient Boosting Regressor
     gb_regressor = GradientBoostingRegressor(n_estimators=100, random_state=0)
     gb_regressor.fit(X_train, y_train)
     # Then we try to predict the Y (Final score) values by using the values of the
      \hookrightarrow X testset
     y_pred = gb_regressor.predict(X_test)
     # Then we calculate the mean squared error and print it
     mse = mean_squared_error(y_test, y_pred)
     print(f"Mean Squared Error: {mse}")
     # Here we can give in the features of a student and our model will try to_{\sqcup}
      ⇒predict what this students final score will be
     # First we make all the input fields for all of our values and turn them in the
      ⇔right value types
```

```
new_student_features = {}
school = input('What school are you attending (For Gabriel Pereira insert GP, U

¬for Mousinho da Silveira insert MS): ').upper().strip()

sex = input('What sex are you (For female insert F, for male insert M): ').
 →upper().strip()
age = input('How old are you: ')
age = int(age)
address = input('Do you live in an urban (insert U) or a rural (insert R)_{\sqcup}
 →neighboorhood: ').upper().strip()
studytime = input('How long do you study: ')
studytime = int(studytime)
absences = input('How manny times were you absent: ')
absences = int(absences)
G1 = input('What was your first score: ')
G1 = int(G1)
G2 = input('What was your second score: ')
G2 = int(G2)
# Because I made it so you have to give a string for the school, sex and \Box
 →address I have an if that sets this to the numbers given to the
⇔corresponding values
# We also add all of these features to the new student features so we can use,
→this to make our prediction
if school == 'GP':
    new_student_features['school'] = 1
elif school == 'MS':
    new_student_features['school'] = 2
if sex == 'F':
    new_student_features['sex'] = 1
elif sex == 'M':
    new_student_features['sex'] = 2
new_student_features['age'] = age
if address == 'U':
    new_student_features['address'] = 1
elif address == 'R':
    new_student_features['address'] = 2
if studytime < 2:</pre>
    new_student_features['studytime'] = 1
elif studytime < 5:</pre>
    new_student_features['studytime'] = 2
elif studytime < 10:</pre>
    new_student_features['studytime'] = 3
else:
    new_student_features['studytime'] = 4
```

```
new_student_features['absences'] = absences
new_student_features['G1'] = G1
new_student_features['G2'] = G2

# We turn the inputted data into a panda dataframe
user_data = pd.DataFrame([new_student_features])

# We reindex the dataframe so that the columns are back to normal
user_data = user_data.reindex(columns=X_train.columns, fill_value=0)

# We reindex the dataframe so that the columns are back to normal
predicted_score = gb_regressor.predict(user_data).round().astype(int)

# We predict and print the score
print(f"Predicted Final Score: {predicted_score[0]:.2f}")
```

Mean Squared Error: 3.8251497091126376

Predicted Final Score: 11.00

5 Support Vector Machine (SVM) Regression

Support Vector Machine (SVM) Regression makes predictions by finding the hyperplane that best fits the data while minimizing the error. In the case of SVM Regression, the goal is to find a hyperplane that has the maximum margin while allowing some level of error (i.e., points that fall outside the margin or are on the wrong side of the hyperplane). These are the steps it uses:

Model Training: Given a dataset with features and target values, the SVM Regression algorithm seeks to find the optimal hyperplane that best fits the data. Unlike SVM classification, where the goal is to separate data into different classes with a maximum margin, SVM Regression aims to find a hyperplane that fits the data as closely as possible while allowing a certain level of error.

Margin and Support Vectors: The margin is defined as the distance between the hyperplane and the closest data points (these data points are called support vectors). The goal is to maximize the margin while minimizing the error. In SVM Regression, some data points are allowed to fall outside the margin, and the algorithm aims to minimize the sum of the errors (the difference between the actual target values and the values predicted by the hyperplane) subject to a user-defined parameter called epsilon ().

Loss Function: SVM Regression uses a loss function that includes the L1 loss (also known as the -insensitive loss) for data points that are within the margin and L2 loss for data points outside the margin. The loss function penalizes points that fall outside the margin based on how far they deviate from the -insensitive tube, where is a user-defined parameter.

Optimization: The SVM Regression algorithm seeks to minimize the loss function while maximizing the margin. This is done by finding the coefficients (weights) for the hyperplane that minimize the loss function while satisfying the margin and constraints.

Prediction: To make a prediction, SVM Regression uses the hyperplane equation with the learned weights and the input features. The predicted value for a new data point is the result of the

hyperplane equation, which is a weighted sum of the input features. The margin and constraints influence how sensitive the model is to deviations from the hyperplane, allowing for a level of error.

6 Code

```
[17]: # Here we do all of our imports
      from sklearn.svm import SVR
      from sklearn.model_selection import train_test_split
      from sklearn.metrics import mean_squared_error
      import pandas as pd
      # We grab the csv file and read it in as a pandas dataframe
      student_df = pd.read_csv('./data/student-mat.csv',delimiter=';')
      # Then we declare all the variables we want to use to make a prediction
      features = ['school', 'sex', 'age', 'address', 'studytime', 'absences', 'G1', |
       # We use thedataframe to make our X and Y values
      X = student df[features]
      y = student_df['G3']
      # Here we turn the values of school, sex and address into numbers
      X = pd.get_dummies(X, columns=['school', 'sex', 'address'], drop_first=True)
      # We split our model 80% training setand 20% testing set
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,__
       →random_state=0)
      # Then we use the SVR from our earlier imports and we fit the model using
       →Support Vector Machine (SVM) Regression
      svr_regressor = SVR(kernel='rbf', C=1.0, epsilon=0.2)
      svr_regressor.fit(X_train, y_train)
      # Then we try to predict the Y (Final score) values by using the values of the
       \hookrightarrow X testset
      y_pred = svr_regressor.predict(X_test)
      # Then we calculate the mean squared error and print it
      mse = mean_squared_error(y_test, y_pred)
      print(f"Mean Squared Error: {mse}")
      # Here we can give in the features of a student and our model will try to_{\sqcup}
       ⇒predict what this students final score will be
      # First we make all the input fields for all of our values and turn them in the
       ⇔right value types
      new_student_features = {}
```

```
school = input('What school are you attending (For Gabriel Pereira insert GP, __

¬for Mousinho da Silveira insert MS): ').upper().strip()

sex = input('What sex are you (For female insert F, for male insert M): ').
→upper().strip()
age = input('How old are you: ')
age = int(age)
address = input('Do you live in an urban (insert U) or a rural (insert R)_
 →neighboorhood: ').upper().strip()
studytime = input('How long do you study: ')
studytime = int(studytime)
absences = input('How manny times were you absent: ')
absences = int(absences)
G1 = input('What was your first score: ')
G1 = int(G1)
G2 = input('What was your second score: ')
G2 = int(G2)
# Because I made it so you have to give a string for the school, sex and
→address I have an if that sets this to the numbers given to the
⇔corresponding values
# We also add all of these features to the new_student_features so we can use_
⇔this to make our prediction
if school == 'GP':
   new_student_features['school'] = 1
elif school == 'MS':
    new_student_features['school'] = 2
if sex == 'F':
    new_student_features['sex'] = 1
elif sex == 'M':
    new_student_features['sex'] = 2
new_student_features['age'] = age
if address == 'U':
    new_student_features['address'] = 1
elif address == 'R':
    new_student_features['address'] = 2
if studytime < 2:</pre>
    new_student_features['studytime'] = 1
elif studytime < 5:</pre>
    new_student_features['studytime'] = 2
elif studytime < 10:</pre>
    new_student_features['studytime'] = 3
else:
    new_student_features['studytime'] = 4
```

```
new_student_features['absences'] = absences
new_student_features['G1'] = G1
new_student_features['G2'] = G2

# We turn the inputted data into a panda dataframe
user_data = pd.DataFrame([new_student_features])

# We reindex the dataframe so that the columns are back to normal
user_data = user_data.reindex(columns=X_train.columns, fill_value=0)

# We predict and print the score
predicted_score = svr_regressor.predict(user_data).round().astype(int)
print(f"Predicted Final Score: {predicted_score[0]}")
```

Mean Squared Error: 4.097789156892933

Predicted Final Score: 12

7 Streamlit app

```
[]: # Here we do all of our imports
             import streamlit as st
             import numpy as np
             import pandas as pd
             from sklearn.linear_model import LinearRegression
             from sklearn.ensemble import GradientBoostingRegressor
             from sklearn.model_selection import train_test_split
             import category_encoders as ce
             from sklearn.svm import SVR
             from sklearn.metrics import r2_score
             # We grab the csv file from my github page and read it in as a pandas dataframe
             github_csv_url = 'https://raw.githubusercontent.com/kieran31415/AI/main/
                 ⇔Homework/Task2/data/student-mat.csv'
             student_df = pd.read_csv(github_csv_url,delimiter=';')
             # Then we declare all the variables we want to use to make a prediction
             independent_vars = ['school', 'sex', 'age', 'address', 'studytime', 'absences', "address', "studytime', 'absences', "age', "address', "studytime', "absences', "age', "address', "age', "
                # Here I made a dropdown in streamlit so you can choose what kind of technique \Box
                \rightarrowyou would like to have a list of. You can also get the R^2 values of all 3_{\square}
                \rightarrow techniques
             regression = st.selectbox('What technique would you like to use?',
                                                                                    ('Linear Regression', 'Gradient Boosting Regressor', u
                →'Support Vector Machine (SVM) Regression', 'Compare R<sup>2</sup> values'))
             # First I am training a model using Linear Regression
```

```
# Linear regression
# Here we turn the values of school, sex and address into numbers
encoder = ce.OrdinalEncoder(cols=['school', 'sex', 'address'])
# We put the transformed data into another dataframe so we can keep our
 ⇔original dataframe
df encoded = encoder.fit transform(student df)
# Now we choose the X using the independent vars and Y (Final Score)
X = df_encoded[independent_vars]
y = df_encoded['G3']
# Then we split the data 80% test data and 20% train data
X_train_L, X_test_L, y_train_L, y_test_L = train_test_split(X, y, test_size=0.
 →2, random_state=0)
# Then we use the linear regression from our earlier imports and we fit the \Box
⇔model using linear regression
model = LinearRegression()
model.fit(X_train_L, y_train_L)
# Here we are going to use Gradient Boosting Regressor as our ML technique
# Gradient Boosting Regressor
# We use the encoded dataframe we made at linear regression to make our X and Y_{1,1}
\rightarrow values
X = df_encoded[independent_vars]
y = df_encoded['G3']
# We split our model 80% training setand 20% testing set
X_train_G, X_test_G, y_train_G, y_test_G = train_test_split(X, y, test_size=0.
→2, random_state=0)
# Then we use the GradientBoostingRegressor from our earlier imports and we fitu
→the model using Gradient Boosting Regressor
gb_regressor = GradientBoostingRegressor(n_estimators=100, random_state=0)
gb_regressor.fit(X_train_G, y_train_G)
# Here we are going to use Support Vector Machine (SVM) Regression as our ML_{\sqcup}
\rightarrow technique
# Support Vector Machine (SVM) Regression
# We use the encoded dataframe we made at linear regression to make our X and Y_{\sqcup}
\rightarrow values
X = df_encoded[independent_vars]
y = df_encoded['G3']
# Then we split the data 80% test data and 20% train data
```

```
X_train_S, X_test_S, y_train_S, y_test_S = train_test_split(X, y, test_size=0.
 →2, random_state=0)
# Then we use the SVR from our earlier imports and we fit the model using
 →Support Vector Machine (SVM) Regression
svr_regressor = SVR(kernel='rbf', C=1.0, epsilon=0.2)
svr_regressor.fit(X_train_S, y_train_S)
# Here we check our dropdown to print the right table
# In this table we print the first 25 records of the predicted set and the \Box
acctual values of the test set using the linear regression model
if regression == 'Linear Regression':
   y_pred_L = model.predict(X_test_L).round().astype(int)
   result_df_L = pd.DataFrame({'Actual': y_test_L[:25], 'Predicted': y_pred_L[:
 ⇒25]})
    st.table(result_df_L)
# In this table we print the first 25 records of the predicted set and the \Box
 →acctual values of the test set using the Gradient Boosting Regressor model
elif regression == 'Gradient Boosting Regressor':
   y_pred_G = gb_regressor.predict(X_test_G).round().astype(int)
   result_df = pd.DataFrame({'Actual': y_test_G[:25], 'Predicted': y_pred_G[:
 →25]})
   st.table(result df)
# In this table we print the first 25 records of the predicted set and the
→acctual values of the test set using the Support Vector Machine (SVM)
 →Regression model
elif regression == 'Support Vector Machine (SVM) Regression':
   y_pred_S = svr_regressor.predict(X_test_S).round().astype(int)
   result df = pd.DataFrame({'Actual': y test S[:25], 'Predicted': y pred S[:
 ⇒25]})
   st.table(result_df)
# Here we print a table to compare the 3 different R2 values
elif regression == 'Compare R<sup>2</sup> values':
    # We calculate the R^2 value of the linear regression model
   y_pred_L = model.predict(X_test_L).round().astype(int)
   r_squared_L = r2_score(y_test_L, y_pred_L)
   # We calculate the R^2 value of the Gradient Boosting Regressor
   y_pred_G = gb_regressor.predict(X_test_G).round().astype(int)
   r_squared_G = r2_score(y_test_G, y_pred_G)
```

```
# We calculate the R^2 value of the linear Support Vector Machine (SVM)_{\sqcup}
 \rightarrowRegression
    y_pred_S = svr_regressor.predict(X_test_S).round().astype(int)
    r_squared_S = r2_score(y_test_S, y_pred_S)
    # Here we put the 3 values together in a pandas framework so we can print_{\sqcup}
 \hookrightarrow it via streamlit
    compare = {'Linear regression':[r_squared_L],'Gradient Boosting Regressor':
 → [r_squared_G], 'Support Vector Machine (SVM) Regression': [r_squared_S]}
    compare_df = pd.DataFrame(data=compare)
    st.text('Compare R<sup>2</sup> values:')
    st.table(compare_df)
# streamlit
# We print the titel
st.title('Predict Final Score.')
# Here we can give in the features of a student and our model will try to_{\sqcup}
 →predict what this students final score will be
# First we make all the input fields for all of our values and turn them in the
 ⇔right value types
new_student_features = {}
school = st.text_input('What school are you attending (For Gabriel PereiraL
 →insert GP, for Mousinho da Silveira insert MS): ').upper().strip()
sex = st.text_input('What sex are you (For female insert F, for male insert M):

¬').upper().strip()
age = st.text_input('How old are you: ')
if age != '':
    age = int(age)
address = st.text_input('Do you live in an urban (insert U) or a rural (insert_
 →R) neighboorhood: ').upper().strip()
studytime = st.text_input('How long do you study: ')
if studytime != '':
    studytime = int(studytime)
absences = st.text_input('How manny times were you absent: ')
if absences != '':
    absences = int(absences)
G1 = st.text_input('What was your first score (0-20): ')
if G1 != '':
G2 = st.text_input('What was your second score (0-20): ')
if G2 != '':
    G2 = int(G2)
# We wait until every value is filled in before printing the predicted values
```

```
if school != '' and sex != '' and age != '' and address != '' and studytime !=__
 \hookrightarrow and absences != '' and G1 != '' and G2 != '':
    # We turn the school, sex and address values into their corresponding values \Box
 →and put all of the inputted values into the new_student_features variable
    if school == 'GP':
        new_student_features['school'] = 1
    elif school == 'MS':
        new_student_features['school'] = 2
    if sex == 'F':
        new_student_features['sex'] = 1
    elif sex == 'M':
        new student features['sex'] = 2
    new_student_features['age'] = age
    if address == 'U':
        new_student_features['address'] = 1
    elif address == 'R':
        new_student_features['address'] = 2
    if studytime < 2:</pre>
        new_student_features['studytime'] = 1
    elif studytime < 5:</pre>
        new_student_features['studytime'] = 2
    elif studytime < 10:</pre>
        new_student_features['studytime'] = 3
        new_student_features['studytime'] = 4
    new_student_features['absences'] = absences
    new_student_features['G1'] = G1
    new_student_features['G2'] = G2
    # We put this data into a pandas dataframe and then make predictions and
 ⇔print these predictions out
    new_student_df = pd.DataFrame([new_student_features])
    1 predicted = model.predict(new student df).round().astype(int)
    text = "With Linear regression I predict a final score of_
 →"+str(l predicted[0])+'.'
    st.text(text)
    g_predicted = gb_regressor.predict(new_student_df).round().astype(int)
    text = "With Gradient Boosting Regressor I predict a final score of ⊔
 →"+str(g_predicted[0])+'.'
    st.text(text)
```

```
s_predicted = svr_regressor.predict(new_student_df).round().astype(int)
text = "With Support Vector Machine (SVM) Regression I predict a final__
score of "+str(s_predicted[0])+'.'
st.text(text)
```