Categorical predictions

This notebook fits machine learning models to predict which students drop out of college.

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import xgboost as xgb

from sklearn.ensemble import GradientBoostingClassifier, RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, f1_score
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.tree import DecisionTreeRegressor
from ucimlrepo import fetch_ucirepo
```

Read in, explore, and prepare the data

Get a sense for the data and prepare them for analyses.

In [2]:
```
# Dataset for student outcomes
# Open, publicly available
# Read more here:
# https://archive.ics.uci.edu/dataset/697/predict+students+dropout+and+academic+success

# Fetch dataset
predict_students_dropout_and_academic_success = fetch_ucirepo(id=697)

# Data (as pandas dataframes)
X = predict_students_dropout_and_academic_success.data.features
y = predict_students_dropout_and_academic_success.data.targets

# Metadata; commenting out because it's a lot!
# This code calling up .metadata is specific to this dataframe,
# would not work in most pandas dataframes
# print(predict_students_dropout_and_academic_success.metadata)
```

```
# Variable information
# NOTE: This code works with this dataframe, but typically when
# working in Pandas, one would pull up information on the
# columns/variables using data_frame_name.info()
print(predict_students_dropout_and_academic_success.variables)
```

```
                                            name     role         type  \
0                                 Marital Status  Feature      Integer   
1                               Application mode  Feature      Integer   
2                              Application order  Feature      Integer   
3                                         Course  Feature      Integer   
4                     Daytime/evening attendance  Feature      Integer   
5                         Previous qualification  Feature      Integer   
6                 Previous qualification (grade)  Feature   Continuous   
7                                    Nacionality  Feature      Integer   
8                         Mother's qualification  Feature      Integer   
9                         Father's qualification  Feature      Integer   
10                           Mother's occupation  Feature      Integer   
11                           Father's occupation  Feature      Integer   
12                               Admission grade  Feature   Continuous   
13                                     Displaced  Feature      Integer   
14                     Educational special needs  Feature      Integer   
15                                        Debtor  Feature      Integer   
16                       Tuition fees up to date  Feature      Integer   
17                                        Gender  Feature      Integer   
18                            Scholarship holder  Feature      Integer   
19                             Age at enrollment  Feature      Integer   
20                                 International  Feature      Integer   
21          Curricular units 1st sem (credited)  Feature      Integer   
22          Curricular units 1st sem (enrolled)  Feature      Integer   
23       Curricular units 1st sem (evaluations)  Feature      Integer   
24          Curricular units 1st sem (approved)  Feature      Integer   
25             Curricular units 1st sem (grade)  Feature      Integer   
26  Curricular units 1st sem (without evaluations)  Feature      Integer   
27          Curricular units 2nd sem (credited)  Feature      Integer   
28          Curricular units 2nd sem (enrolled)  Feature      Integer   
29       Curricular units 2nd sem (evaluations)  Feature      Integer   
30          Curricular units 2nd sem (approved)  Feature      Integer   
31             Curricular units 2nd sem (grade)  Feature      Integer   
32  Curricular units 2nd sem (without evaluations)  Feature      Integer   
33                             Unemployment rate  Feature   Continuous   
34                                Inflation rate  Feature   Continuous   
35                                           GDP  Feature   Continuous   
36                                        Target   Target  Categorical   

       demographic                                        description units  \
0   Marital Status  1 – single 2 – married 3 – widower 4 – divorce...  None   
1             None  1 - 1st phase - general contingent 2 - Ordinan...  None   
```

```
2              None  Application order (between 0 - first choice; a...  None
3              None  33 - Biofuel Production Technologies 171 - Ani...  None
4              None                          1 – daytime 0 - evening  None
5   Education Level  1 - Secondary education 2 - Higher education -...  None
6              None  Grade of previous qualification (between 0 and...  None
7       Nationality  1 - Portuguese; 2 - German; 6 - Spanish; 11 - ...  None
8   Education Level  1 - Secondary Education - 12th Year of Schooli...  None
9   Education Level  1 - Secondary Education - 12th Year of Schooli...  None
10       Occupation  0 - Student 1 - Representatives of the Legisla...  None
11       Occupation  0 - Student 1 - Representatives of the Legisla...  None
12             None              Admission grade (between 0 and 200)  None
13             None                                   1 – yes 0 – no  None
14             None                                   1 – yes 0 – no  None
15             None                                   1 – yes 0 – no  None
16             None                                   1 – yes 0 – no  None
17           Gender                              1 – male 0 – female  None
18             None                                   1 – yes 0 – no  None
19              Age                     Age of studend at enrollment  None
20             None                                   1 – yes 0 – no  None
21             None  Number of curricular units credited in the 1st...  None
22             None  Number of curricular units enrolled in the 1st...  None
23             None  Number of evaluations to curricular units in t...  None
24             None  Number of curricular units approved in the 1st...  None
25             None  Grade average in the 1st semester (between 0 a...  None
26             None  Number of curricular units without evalutions ...  None
27             None  Number of curricular units credited in the 2nd...  None
28             None  Number of curricular units enrolled in the 2nd...  None
29             None  Number of evaluations to curricular units in t...  None
30             None  Number of curricular units approved in the 2nd...  None
31             None  Grade average in the 2nd semester (between 0 a...  None
32             None  Number of curricular units without evalutions ...  None
33             None                            Unemployment rate (%)  None
34             None                               Inflation rate (%)  None
35             None                                              GDP  None
36             None  Target. The problem is formulated as a three c...  None

   missing_values
0              no
1              no
2              no
3              no
4              no
```

```
5           no
6           no
7           no
8           no
9           no
10          no
11          no
12          no
13          no
14          no
15          no
16          no
17          no
18          no
19          no
20          no
21          no
22          no
23          no
24          no
25          no
26          no
27          no
28          no
29          no
30          no
31          no
32          no
33          no
34          no
35          no
36          no
```

In [3]:

```
# Some integer features should be treated as categorical.
# Let's get some descriptive statistics on some of the
# features to better understand why they might be categories.
X[[
    "Application mode",
    "Mother's qualification",
    "Father's qualification",
    "Nacionality",
    "Marital Status",
```

```
    ]].describe()
# Looking at Marital Status, we see a maximum of 6, so this is not a binary
# 0/1 feature. Instead it's a categorical feature that we need to set as
# a category in the data.
```

Out[3]:

	Application mode	Mother's qualification	Father's qualification	Nacionality	Marital Status
count	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000
mean	18.669078	19.561935	22.275316	1.873192	1.178571
std	17.484682	15.603186	15.343108	6.914514	0.605747
min	1.000000	1.000000	1.000000	1.000000	1.000000
25%	1.000000	2.000000	3.000000	1.000000	1.000000
50%	17.000000	19.000000	19.000000	1.000000	1.000000
75%	39.000000	37.000000	37.000000	1.000000	1.000000
max	57.000000	44.000000	44.000000	109.000000	6.000000

In [4]:

```
# For simplicity, let's drop most of the categorical features
features_to_drop = [
    "Application mode",
    "Mother's qualification",
    "Father's qualification",
    "Nacionality",
    "Mother's occupation",
    "Father's occupation",
    "Previous qualification",
    "Course",
]
X = X.drop(columns=features_to_drop)
```

In [5]:

```
# We will transform the categorical feature Marital Status into a series of
# binary columns for each category but one
# This method drops one of the categories to avoid redudancy with the
# columns for the other categories
X = pd.get_dummies(X, columns=['Marital Status'], drop_first=True)
```

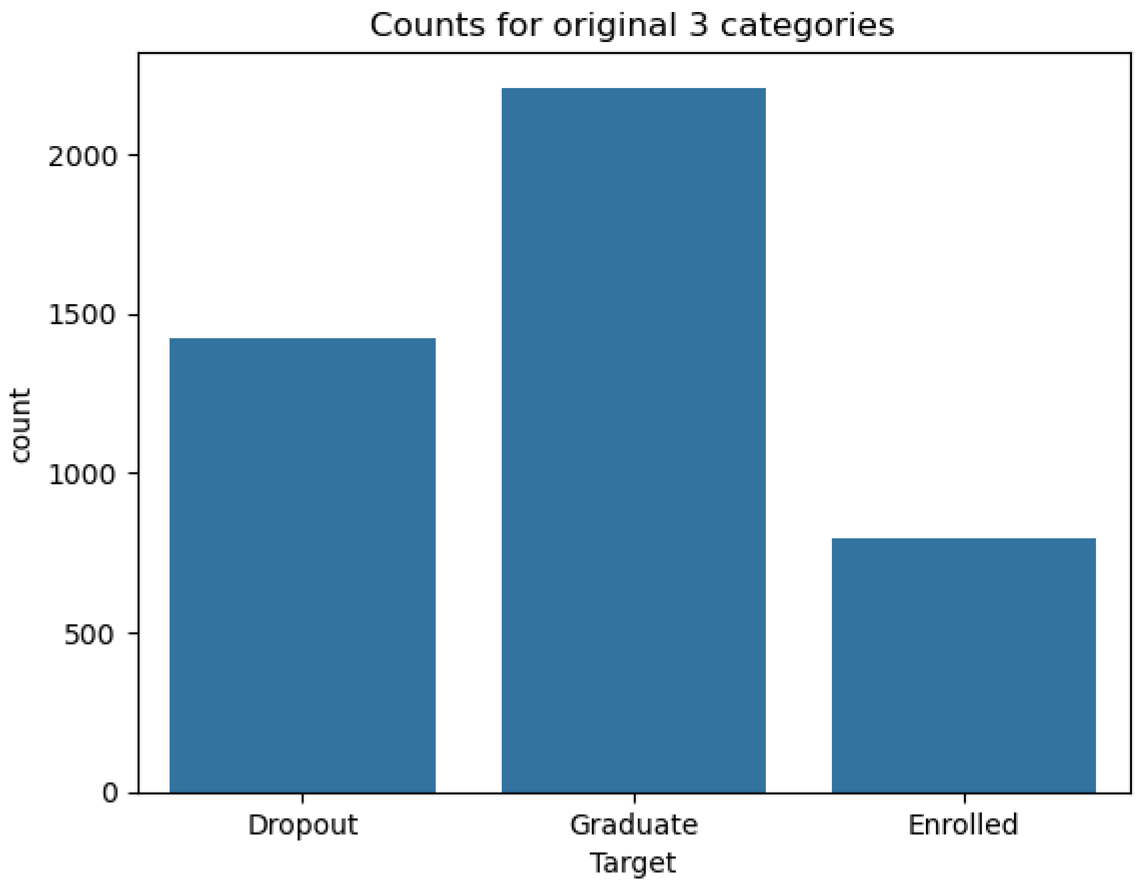
In [6]:
```
# Let's look at our simplified data
# Notice the columns for Martial Status
# (with value of 1 missing, that's the reference
# category)
print(X.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4424 entries, 0 to 4423
Data columns (total 32 columns):
 #   Column                                        Non-Null Count  Dtype  
---  ------                                        --------------  -----  
 0   Application order                             4424 non-null   int64  
 1   Daytime/evening attendance                    4424 non-null   int64  
 2   Previous qualification (grade)                4424 non-null   float64
 3   Admission grade                               4424 non-null   float64
 4   Displaced                                     4424 non-null   int64  
 5   Educational special needs                     4424 non-null   int64  
 6   Debtor                                        4424 non-null   int64  
 7   Tuition fees up to date                       4424 non-null   int64  
 8   Gender                                        4424 non-null   int64  
 9   Scholarship holder                            4424 non-null   int64  
 10  Age at enrollment                             4424 non-null   int64  
 11  International                                 4424 non-null   int64  
 12  Curricular units 1st sem (credited)           4424 non-null   int64  
 13  Curricular units 1st sem (enrolled)           4424 non-null   int64  
 14  Curricular units 1st sem (evaluations)        4424 non-null   int64  
 15  Curricular units 1st sem (approved)           4424 non-null   int64  
 16  Curricular units 1st sem (grade)              4424 non-null   float64
 17  Curricular units 1st sem (without evaluations)  4424 non-null   int64  
 18  Curricular units 2nd sem (credited)           4424 non-null   int64  
 19  Curricular units 2nd sem (enrolled)           4424 non-null   int64  
 20  Curricular units 2nd sem (evaluations)        4424 non-null   int64  
 21  Curricular units 2nd sem (approved)           4424 non-null   int64  
 22  Curricular units 2nd sem (grade)              4424 non-null   float64
 23  Curricular units 2nd sem (without evaluations)  4424 non-null   int64  
 24  Unemployment rate                             4424 non-null   float64
 25  Inflation rate                                4424 non-null   float64
 26  GDP                                           4424 non-null   float64
 27  Marital Status_2                              4424 non-null   bool   
 28  Marital Status_3                              4424 non-null   bool   
 29  Marital Status_4                              4424 non-null   bool   
 30  Marital Status_5                              4424 non-null   bool   
 31  Marital Status_6                              4424 non-null   bool   
dtypes: bool(5), float64(7), int64(20)
memory usage: 954.9 KB
None
```

In [7]:
```
# Have 3 categories for the target, but for this demonstration,
# want just 2 for simplicity
# Recoding Target into 2 labeled and 2 numeric categories
# For numeric categories, 1 = 'Late grad or drop-out'
y_recode = y.copy()
y_recode['TargetLabel'] = np.where(y_recode['Target'] == 'Graduate', 'On-time grad', 'Late grad or drop-out')
y_recode['TargetNumeric'] = np.where(y_recode['Target'] == 'Graduate', 0, 1)
```

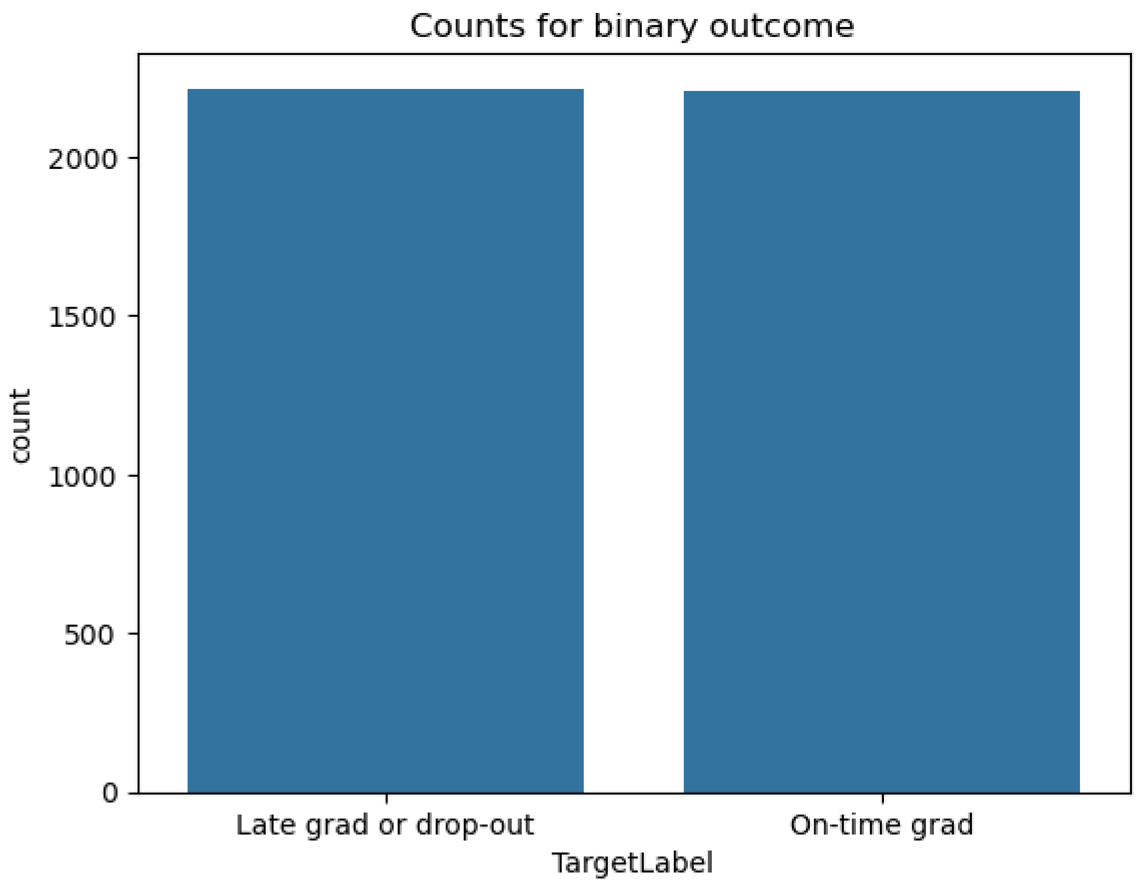
In [8]:
```
# Let's look at the original categories
sns.countplot(data=y, x='Target').set(title="Counts for original 3 categories")
```

Out[8]:
```
[Text(0.5, 1.0, 'Counts for original 3 categories')]
```



In [9]:
```
# And now let's look at our binary categories
sns.countplot(data=y_recode, x='TargetLabel').set(title="Counts for binary outcome")
```

Out[9]: [Text(0.5, 1.0, 'Counts for binary outcome')]



Things to note from the above:

- When we have three categories, they are quite imbalanced.
- With two categories, the balance is amazing!

We will continue with two categories, but I've left code commented out that would allow you to run the models on all three categories. Note that different approaches have relative benefits depending on the nature of your data.

You can read more later here: https://medium.com/@hassaanidrees7/gradient-boosting-vs-random-forest-which-ensemble-method-should-you-use-9f2ee294d9c6

In [10]:
```
# Set aside 20% of the data as final testing dataset
# NOTE: The commented out part below is in case you want
# to build models predicting all 3 categories if you
# have extra time or want to do more after the presentation
X_modeling, X_test, y_modeling, y_test = train_test_split(
    X, y_recode['TargetNumeric'], test_size=0.20, random_state=55)
# X_modeling, X_test, y_modeling, y_test = train_test_split(
#     X, np.array(y), test_size=0.20, random_state=55)
```

In [11]:
```
# Get training and validation data
X_train, X_validate, y_train, y_validate = train_test_split(
    X_modeling, y_modeling, test_size=0.20, random_state=55)
```

Fit the random forest and gradient boost models

The following cells fit the models with default hyperparameters(not hyperparameters we choose). We only set the random_state for reproducibility. Hyperparameter tuning comes later!

- For future reference, you can read up on all of the hyperparamters and their defaults for GradientBoostingClassifier here: https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.GradientBoostingClassifier.html
- And here is where you can read up on all of the hyperparameters and their defaults for RandomForestClassfier, for future reference: https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

In [12]:
```
# Fit a random forest classifier
rand_for = RandomForestClassifier(random_state=55)
rand_for.fit(X_train, y_train)

# Get predictions
rand_for_preds = rand_for.predict(X_validate)

# Print f1 score, classification report
# print('Rand forest f1 score: ', f1_score(rand_for_preds, y_validate, average='macro'))
print('Rand forest f1 score: ', round(f1_score(rand_for_preds, y_validate), 4))
print('Rand forest classification_report: \n', classification_report(rand_for_preds, y_validate))
```

```
# This "extra" step is just to make the code work whether or not
# people run some "optional" code below that I have commented out
best_model_rand_for = rand_for
```

```
Rand forest f1 score:  0.8539
Rand forest classification_report:
               precision    recall  f1-score   support

           0       0.91      0.81      0.86       377
           1       0.80      0.91      0.85       331

    accuracy                           0.85       708
   macro avg       0.86      0.86      0.85       708
weighted avg       0.86      0.85      0.85       708
```

In [13]:

```
# Fit a gradient boosting classifier
grad_boost = GradientBoostingClassifier(random_state=55)
grad_boost.fit(X_train, y_train)

# Get predictions
grad_boost_preds = grad_boost.predict(X_validate)

# Print f1 score, classification report
# NOTE: The commented out part below is in case you want
# to build models predicting all 3 categories if you
# have extra time or want to do more after the presentation
# print('Grad boost f1 score: ', round(f1_score(grad_boost_preds, y_validate, average='macro'), 4))
print('Grad boost f1 score: ', round(f1_score(grad_boost_preds, y_validate), 4))
print('Grad boost classification report: \n', classification_report(grad_boost_preds, y_validate))
```

```
Grad boost f1 score:  0.8357
Grad boost classification report:
               precision    recall  f1-score   support

           0       0.89      0.79      0.84       376
           1       0.79      0.89      0.84       332

    accuracy                           0.84       708
   macro avg       0.84      0.84      0.84       708
weighted avg       0.84      0.84      0.84       708
```

Hyperparameter tune the gradient boosting model This is very simple hyperparameter tuning on just a few hyperparameters for demonstration purposes. We focus on the gradient boosting model because (spoiler!) the hyperparameter tuning changes the metrics more with this model compared to the random forest. Note that we use GridSearchCV, which tests out all combinations. If you end up doing more with machine learning, I recommend looking up Optuna, which strategically chooses which combinations of hyperparameters to focus on for more thorough hyperparameter tuning that is relatively fast.

In [14]:
```
# Hyperparameter tuning for grad boost
# Code adapted from this source:
# https://www.geeksforgeeks.org/how-to-tune-hyperparameters-in-gradient-boosting-algorithm/

# If you have extra time, you could play around with changing
# the parts with comments and see if you can do even better!

# Define the parameter grid for GridSearchCV
param_grid_grad_boost = {
    'n_estimators': [50, 100, 200], # Could try different and/or additional numbers here
    'learning_rate': [0.05, 0.1, 0.2, 0.3], # And here
    'max_depth': [2, 3, 4], # And here
}

# Initialize GridSearchCV
# NOTE: The commented out part below is in case you want
# to build models predicting all 3 categories if you
# have extra time or want to do more after the presentation
# grid_search_grad_boost = GridSearchCV(estimator=grad_boost, param_grid=param_grid_grad_boost, cv=5, scoring='f1_mac
grid_search_grad_boost = GridSearchCV(estimator=grad_boost, param_grid=param_grid_grad_boost, cv=5, scoring='f1', n_j

# Fit the model to the training data using GridSearchCV
grid_search_grad_boost.fit(X_train, y_train)

# Get the best parameters and best model
best_params_grad_boost = grid_search_grad_boost.best_params_
best_model_grad_boost = grid_search_grad_boost.best_estimator_

# Make predictions on the test set using the best model
# The default for GridSearchCV is to update the model grad_boost
# to have the tuned hyperparameters, so the following will
# give predictions from the tuned model now
y_pred_best_grad_boost = best_model_grad_boost.predict(X_validate)

# Evaluate the best model
# NOTE: The commented out part below is in case you want
# to build models predicting all 3 categories if you
```

```
# have extra time or want to do more after the presentation
# f1_best_grad_boost = f1_score(y_validate, y_pred_best_grad_boost, average='macro')
f1_best_grad_boost = f1_score(y_validate, y_pred_best_grad_boost)
class_report_best_grad_boost = classification_report(y_validate, y_pred_best_grad_boost)

# Print the results
print("Grad boost best parameters: ", best_params_grad_boost)
print(f"Grad boost best model f1 score:  {round(f1_best_grad_boost, 4)}")
print(f"Grad boost best model classification report: \n{class_report_best_grad_boost}")
```

```
Grad boost best parameters:  {'learning_rate': 0.3, 'max_depth': 2, 'n_estimators': 100}
Grad boost best model f1 score:  0.8575
Grad boost best model classification report: 
              precision    recall  f1-score   support

           0       0.81      0.91      0.86       334
           1       0.91      0.81      0.86       374

    accuracy                           0.86       708
   macro avg       0.86      0.86      0.86       708
weighted avg       0.86      0.86      0.86       708
```

In [15]:

```
# Commented out for time
# You can uncomment and run if you finish early or after the session
# To uncomment: select everything in this cell below here and use
# the keyboard shortcut Ctrl + c

# # Hyperparameter tuning for random forest classifier
# # Code adapted from this source (though note that I found some errors and other issues):
# # https://www.geeksforgeeks.org/random-forest-hyperparameter-tuning-in-python/

# # Define the parameter grid for GridSearchCV
# param_grid_rand_for = {
#     'n_estimators': [50, 100, 200],
#     'max_features': ['sqrt', 'log2'],
#     'max_depth': [None, 2, 3],
# }

# # Initialize GridSearchCV for random forest classifier
# # grid_search_rand_for = GridSearchCV(estimator=rand_for, param_grid=param_grid_rand_for, cv=5, scoring='f1_macro',
# grid_search_rand_for = GridSearchCV(estimator=rand_for, param_grid=param_grid_rand_for, cv=5, scoring='f1', n_jobs=
```

```
# # Fit the model to the training data using GridSearchCV
# grid_search_rand_for.fit(X_train, y_train)

# # Get the best parameters and best model
# best_params_rand_for = grid_search_rand_for.best_params_
# best_model_rand_for = grid_search_rand_for.best_estimator_

# # Make predictions on the test set using the best model
# # The default for GridSearchCV is to update the model grad_boost
# # to have the tuned hyperparameters, so the following will
# # give predictions from the tuned model now
# y_pred_best_rand_for = best_model_rand_for.predict(X_validate)

# # Evaluate the best model
# # NOTE: The commented out part below is in case you want
# # to build models predicting all 3 categories if you
# # have extra time or want to do more after the presentation
# # f1_best_rand_for = f1_score(y_validate, y_pred_best_grad_boost, average='macro')
# f1_best_rand_for = f1_score(y_validate, y_pred_best_rand_for)
# class_report_best_rand_for = classification_report(y_validate, y_pred_best_rand_for)

# # Print the results
# print("Random forest best parameters: ", best_params_rand_for)
# print(f"Rand forest best model f1 score:  {round(f1_best_rand_for, 4)}")
# print(f"Rand forest best model classification report: \n{class_report_best_rand_for}")
```

Discuss what you see!

What do you see when you compare the default model to the tuned model?

- Did hyperparamter tuning improve your f1 score?
- If so, by how much?
- What are your reactions to these results?

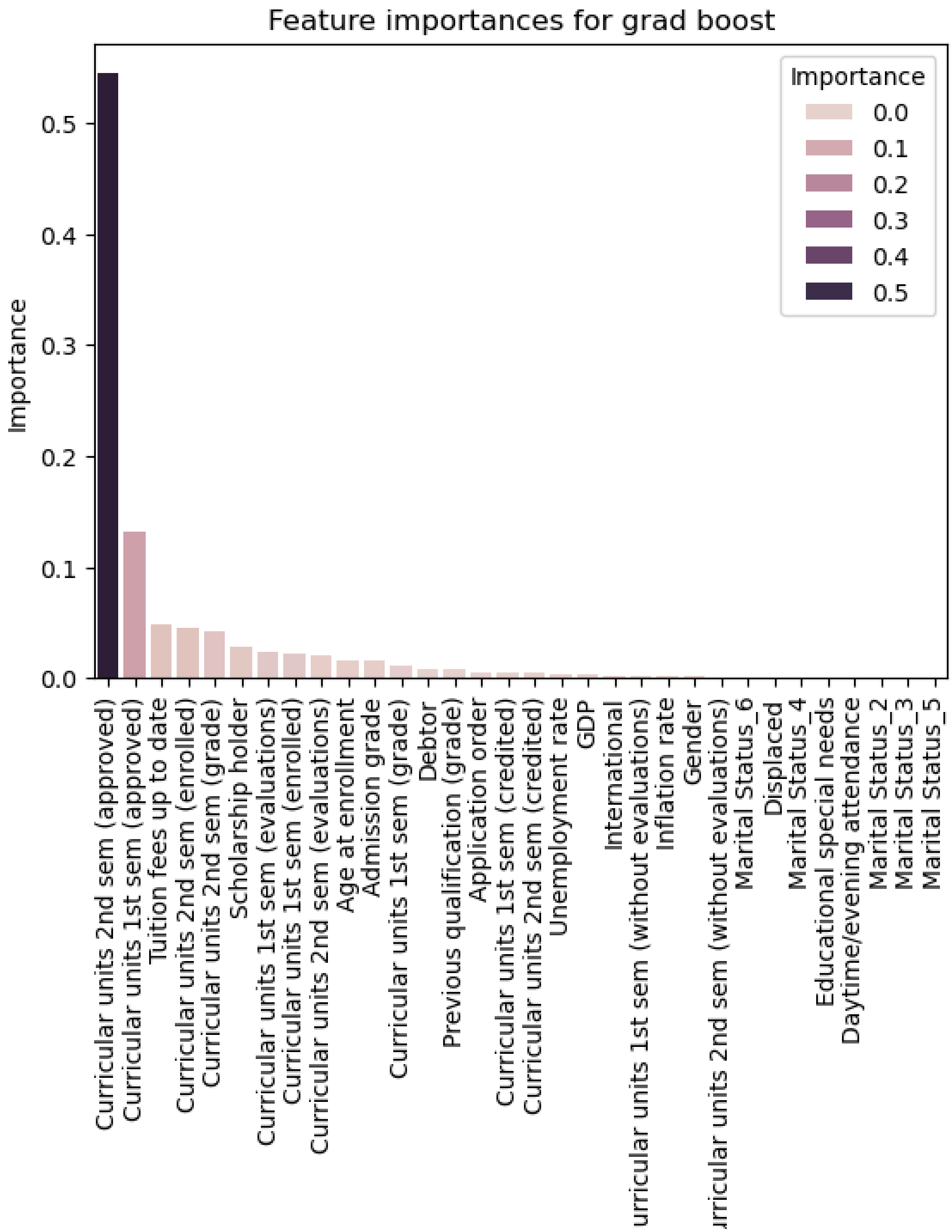
Feature importances

A critique of machine learning is that it can lack transperency. We can add some transparency but pulling up feature importances. These are *not* the same as parameters you might see in a logistic regression model. Rather, they are values that tell you which features (or predictors or independent variables) were most influential in the predicitons from the model.

In [16]:
```
# Boosting model feature importances
grad_boost_importances = best_model_grad_boost.feature_importances_
grad_boost_importances_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': grad_boost_importances
}).sort_values(
    axis=0,
    by='Importance',
    ascending=False
)
```

In [17]:
```
# Creating the data viz
g_boost = sns.barplot(
    grad_boost_importances_df,
    x='Feature',
    y='Importance',
    hue='Importance'
)
# Rotating the labels for readability
g_boost.tick_params(axis='x', rotation=90)
g_boost.set(title="Feature importances for grad boost")
```

Out[17]:
```
[Text(0.5, 1.0, 'Feature importances for grad boost')]
```


Feature importances for grad boost
Importance
0.0
0.1
0.2
0.3
0.4
0.5
Importance
0.0
0.1
0.2
0.3
0.4
0.5
Curricular units 2nd sem (approved)
Curricular units 1st sem (approved)
Tuition fees up to date
Curricular units 2nd sem (enrolled)
Curricular units 2nd sem (grade)
Scholarship holder
Curricular units 1st sem (evaluations)
Curricular units 1st sem (enrolled)
Curricular units 2nd sem (evaluations)
Age at enrollment
Admission grade
Curricular units 1st sem (grade)
Debtor
Previous qualification (grade)
Application order
Curricular units 1st sem (credited)
Curricular units 2nd sem (credited)
Unemployment rate
GDP
International
urricular units 1st sem (without evaluations)
Inflation rate
Gender
urricular units 2nd sem (without evaluations)
Marital Status_6
Displaced
Marital Status_4
Educational special needs
Daytime/evening attendance
Marital Status_2
Marital Status_3
Marital Status_5

In [18]:
```
# Commented out for time, you can uncomment
# Random forest model feature importances
# rand_for_importances = best_model_rand_for.feature_importances_
# rand_for_importances_df = pd.DataFrame({
#     'Feature': X_train.columns,
#     'Importance': rand_for_importances
# }).sort_values(
#     axis=0,
#     by='Importance',
#     ascending=False
# )
```

In [19]:
```
# Commented out for time, you can uncomment
# Creating the data viz, then rotating the labels and setting a title
# g_rand_for = sns.barplot(
#     rand_for_importances_df,
#     x='Feature',
#     y='Importance',
#     hue='Importance'
# )
# g_rand_for.tick_params(axis='x', rotation=90)
# g_rand_for.set(title="Feature importances for random forest")
```

Discuss feature importances

- What does the above tell you about the features that contributed the most information to predictions from the model?
- Anything that surprised you?
- Based on these importances, are there features you would leave out of future models for simplicity?

The final step!

Once you have done all you plan to do to improve your predictions with your model, you can see how it runs on the "hold out" or "out of bag" data, the data we've never looked at before. This gives us a better sense of how we expect the model to perform in real time with data it has never "seen" before.

Below, we'll get predictions and then compute the relevant metrics for the unseen data as a final gauge of how well we expect our models to perform in the real world, both for the (untuned) random forest and for the tuned gradient boosting model.

In [20]:
```
# NOTE: Unless you uncommented the part that hyperparameter
# tunes the random forest, this is for the untuned model

# Random forest
# Getting predictions from hold out data first
y_pred_hold_out_rand_for = best_model_rand_for.predict(X_test)

# Evaluate the best model
f1_hold_out_rand_for = f1_score(y_test, y_pred_hold_out_rand_for)
class_report_hold_out_rand_for = classification_report(y_test, y_pred_hold_out_rand_for)

# Print the results
print(f"Rand forest f1 score from hold out data:  {round(f1_hold_out_rand_for, 4)}")
print(f"Rand forest best model classification report: \n{class_report_hold_out_rand_for}")
```

```
Rand forest f1 score from hold out data:  0.8492
Rand forest best model classification report: 
              precision    recall  f1-score   support

           0       0.82      0.88      0.85       422
           1       0.88      0.82      0.85       463

    accuracy                           0.85       885
   macro avg       0.85      0.85      0.85       885
weighted avg       0.85      0.85      0.85       885
```

In [21]:
```
# Gradient boost
# Getting predictions from hold out data first
y_pred_hold_out_grad_boost = best_model_grad_boost.predict(X_test)

# Evaluate the best model
f1_hold_out_grad_boost = f1_score(y_test, y_pred_hold_out_grad_boost)
class_report_hold_out_grad_boost = classification_report(y_test, y_pred_hold_out_grad_boost)

# Print the results
print(f"Grad boost f1 score from hold out data:  {round(f1_hold_out_grad_boost, 4)}")
print(f"Grad boost best model classification report: \n{class_report_hold_out_grad_boost}")
```

```
Grad boost f1 score from hold out data:  0.8422
Grad boost best model classification report:
              precision    recall  f1-score   support

           0       0.80      0.89      0.84       422
           1       0.89      0.80      0.84       463

    accuracy                           0.84       885
   macro avg       0.85      0.84      0.84       885
weighted avg       0.85      0.84      0.84       885
```

Discuss the final predictions

- Which approach (random forest or gradient boosting) performed better on the unseen testing data?
- What are your reactions to this finding?

Additional things you can try on your own

1. Uncomment out the sections we "skipped" for random forest, including hyperparameter tuning and feature importances.
2. Uncommended out the parts that would allow you to run the models predicting all three original categories.

For anything extra you do, what do you see? What surprises you? What lessons might you take from these findings to guide you in future machine learning modeling?