Scenario 2: CROP RECOMMENDATION SYSTEM

Forest Department of Karnataka is working to protect endangered species in a tropical rainforest. They have access to a dataset of deforestation events and a shapefile of the rainforest boundaries. They want to identify areas of the rainforest that are most at risk of deforestation and focus their conservation efforts on those areas. Develop a model to solve the problem using Python and also explain your solution with complete documentation. Upload the solution ode and documentation in the GitHub Public Repository. Share the code, visualization, GitHub Link and other stuff in the Google Classroom.

Introduction

This dataset contain historical satellite data about deforestaion occured in Amazônia. Basically it contains deforestation rates in counties located in Amazônia rainforest. The data was taken from the brazilian National Institute for Space Research (INPE) more specifically I took the data from a data lake created by INPE on the BigQuery.The dataset is available for access here.

- Counties.csv

Column Name	Type	Description
Nome_Microrregião	string	County Name
Código Município Completo	int	County Id which the first two numbers represent the state of which the county is located

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- data.csv | Column Name | Type | Description | | --- | --- | --- | | ano | int | Year | | id_municipio | int | County Id it is the same as the one located in the table Counties.csv | | area | int | Total area measured | | desmatado | float | Total area deforestaed | | incremento | float | Area measured after thus it is a increment to the previous measure| | floresta | float | total forest area | | nuvem | float | area covered by the clouds | | nao_observado | float | non-measured area | | nao_floresta | float | non-forest area | | hidrografia | float | hydrographic area |

- states.csv

Column Name	Type	Description
estados_ido	int	State id
Estados	int	State name

```
import pandas as pd
import numpy as np
from collections import Counter
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDRegressor
from sklearn.ensemble import BaggingRegressor
from sklearn.ensemble import VotingRegressor
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn import metrics
```

Data Loading

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
df = pd.read_csv("/content/drive/MyDrive/deforestationdata/data.csv")
mun = pd.read_csv("/content/drive/MyDrive/deforestationdata/Counties.csv",sep = ';')
states = pd.read_csv("/content/drive/MyDrive/deforestationdata/states.csv")
```

```
df.head()
```

ano	id_municipio	area	desmatado	incremento	floresta	nuvem	nao_observado	nao_floresta	hidrografia	municipios	estados

```
mun.head()
```

	Nome_Microrregião	Código Município Completo
0	Cacoal	1100015
1	Cacoal	1100379
2	Ariquemes	1100403
3	Alvorada D'Oeste	1100346
4	Ariquemes	1100023

```
states.head()
```

	estados_id	Estados
0	11	Rondônia
1	12	Acre
2	13	Amazonas
3	14	Roraima
4	15	Pará

The first thing that we're going to do is to make two new columns in the data.csv table this columns will cotain the county name and state. Thus we'll need the Counties.csv and states.csv tables to make it.

```
def call(number):
    """This fuction will use the first two characters of a number
    and return all the matches from the states["estados_id"] dataframe"""
    num = str(number)[0:2]
    num = int(num)
    return states[states["estados_id"] == num]


def transform(df):
    """It creates two lists with the name of the county and its state"""
    munic = []
    esta = []
    for i in range(len(df["id_municipio"])):
        ind = mun[mun["Código Município Completo"] == df["id_municipio"][i]]["Nome_Microrregião"].index[0]
        nome_mun = mun[mun["Código Município Completo"] == df["id_municipio"][i]]["Nome_Microrregião"][ind]

        ind_es = mun[mun["Código Município Completo"] == df["id_municipio"][i]]["Código Município Completo"][ind]
        m = call(ind_es)["Estados"].index[0]
        nome_est = call(ind_es)["Estados"][m]

        munic.append(nome_mun)
        esta.append(nome_est)
    return munic, esta


def stats_year(df,nome,Mean):
    """it returns the total sum of the nome column grouped
    by the ano column"""
    sum = df[["ano",nome]].groupby(['ano']).sum()
    media = sum[nome].mean()
    vals = []
    if Mean == False:
        for k in sum[nome]:
            vals.append(k)
    else:
        for k in sum[nome]:
            vals.append(k/media)
    return np.array(vals),sum.index


lista_mun , lista_est = transform(df) #lets add the new columns to our dataset
df["municipios"] = lista_mun
df["estados"] = lista_est
```

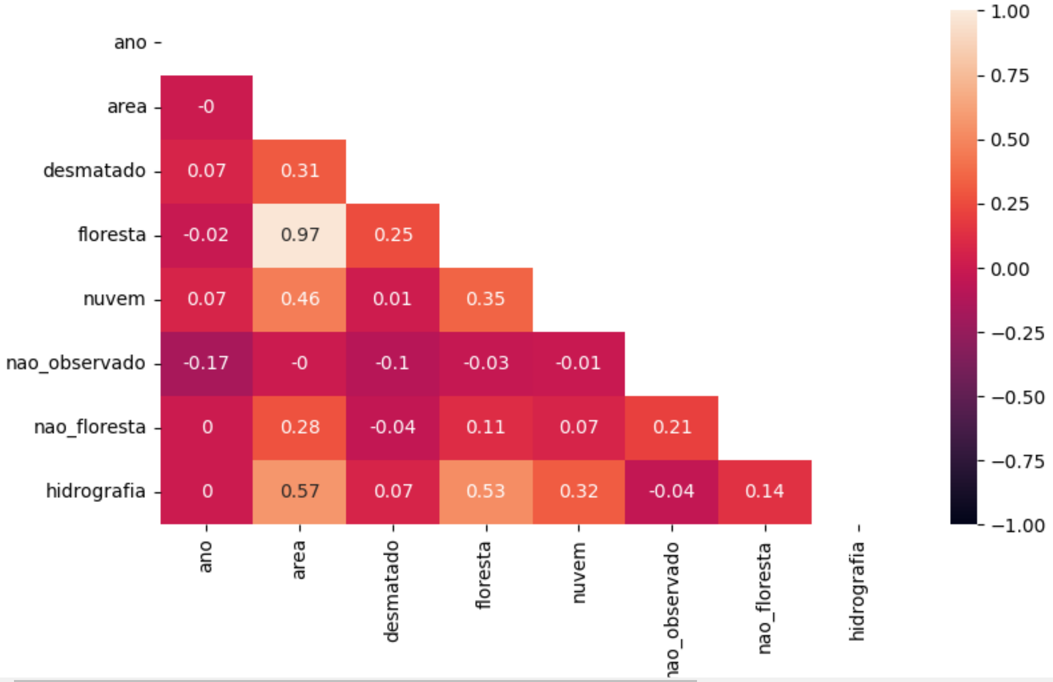
Geting Statistical Insights

In this section we'll study the correlation between some variables. We'll also analyze the relationship between deforestaion and forest area.

```
new = df[["ano","area","desmatado","floresta","nuvem","nao_observado","nao_floresta","hidrografia","estados","municipios"]]
corr = round(new.corr(),2)
mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(9, 5))

sns.heatmap(corr, mask=mask, vmin=-1,vmax=1,annot = True)
```

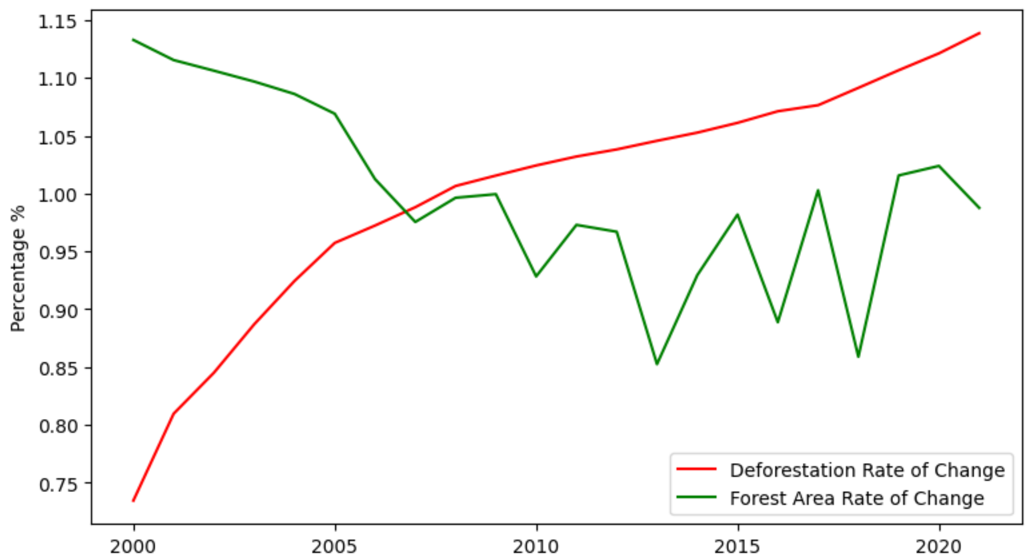
```
<ipython-input-9-859b9da22407>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ver
  corr = round(new.corr(),2)
<Axes: >
```



As we see from the correlation matrix above, there is a clear correlation between area and floresta (forest) which is expected since the more area the more forest it can have in. Besides there is a certain correlation between area and desmatado (deforestation) which is again expected.

```
lista1, anos1 = stats_year(df,"desmatado",True)
lista2, anos2 = stats_year(df,"floresta",True)
plt.figure(figsize=(9, 5))
plt.plot(list(anos1),lista1,"r", label="Deforestation Rate of Change")
plt.plot(list(anos2),lista2,"g", label="Forest Area Rate of Change")
plt.ylabel("Percentage %")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7ceadd858ee0>
```



The line plot shows to us that there is a anti-correlationship between deforestation and forest area. But this relationship is unclear from 2005 and beyond because the Forest Area starts to random variate it may be due to social-political response and bias measures.

Findind The Counties with more deforestation

Lets now find the counties with more deforestation for it we need create a new dataset with the deforestation rate and its respectively county.

```
anos = list(set(df["ano"]))
year = []
desmat = []
munic = []
esta = []
for ano in anos:

  new = df[df["ano"]==ano]
  new  = new.sort_values(by=['desmatado'], ascending=False)

  year.append(np.array(list(new.copy().iloc[0:10]["ano"])[:]))
  desmat.append(np.array(list(new.copy().iloc[0:10]["desmatado"])[:]))
  munic.append(np.array(list(new.copy().iloc[0:10]["municipios"])[:]))
  esta.append(np.array(list(new.copy().iloc[0:10]["estados"])[:]))
```

```
dic = dict()
dic["ano"] = np.array(year).reshape(1,-1)[0]
dic["estado"] = np.array(esta).reshape(1,-1)[0]
dic["desmatado"] = np.array(desmat).reshape(1,-1)[0]
dic["municipio"] = np.array(munic).reshape(1,-1)[0]
novo = pd.DataFrame(dic)
novo
```

	ano	estado	desmatado	municipio
0	2000	Pará	7212.3	Paragominas
1	2000	Pará	7037.4	São Félix do Xingu
2	2000	Pará	5818.9	Marabá
3	2000	Mato Grosso	5520.7	Arinos
4	2000	Maranhâo	5373.3	Pindaré
...	...	...	...	...
215	2021	Pará	8616.0	Tucuruí
216	2021	Mato Grosso	8272.2	Arinos
217	2021	Pará	7528.9	São Félix do Xingu
218	2021	Pará	7353.5	Conceição do Araguaia
219	2021	Pará	7274.2	Itaituba

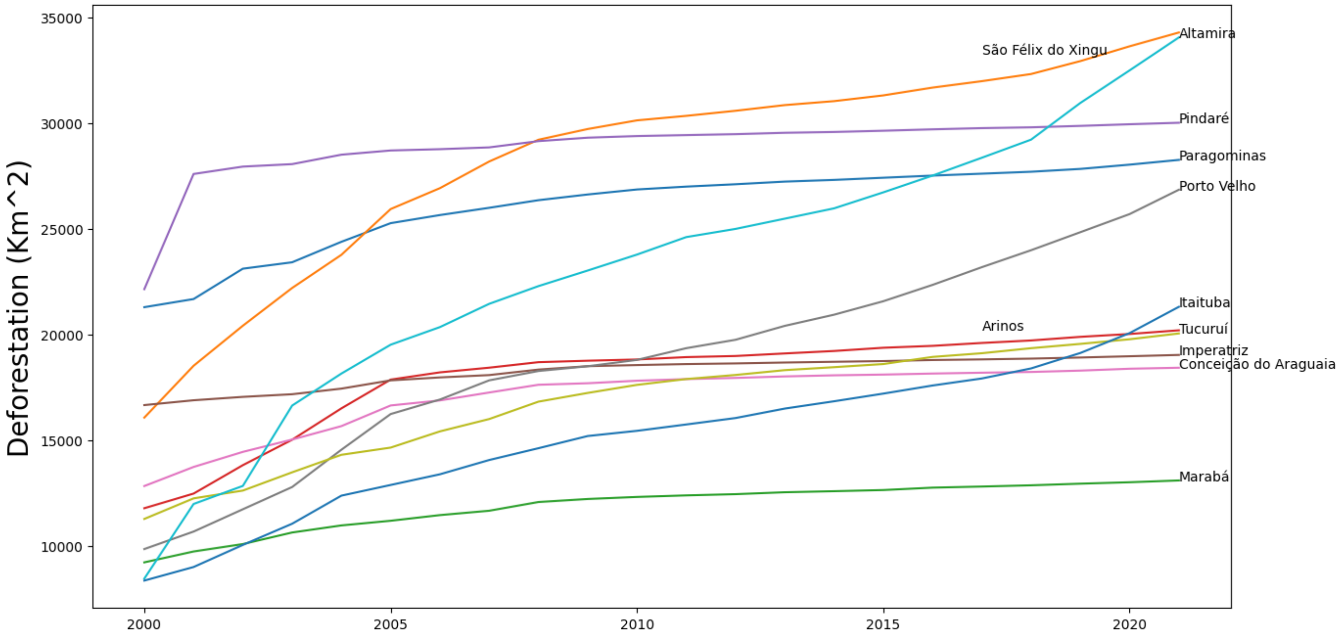
220 rows × 4 columns

```
muns = list(Counter(novo["municipio"]))
mat = []
for i in range(len(muns)):

  data = df[df["municipios"] == muns[i]]
  mat.append(stats_year(data,"desmatado",False)[0])
```

```
plt.figure(figsize=(15, 8))
for i in range(len(muns)):

  if muns[i] == "São Félix do Xingu":
    plt.plot(list(set(novo.ano)),mat[i])
    plt.text(list(set(novo.ano))[-1]-4, mat[i][-1]-1000, str(muns[i]), fontsize = 10)
  elif muns[i] == "Arinos":
    plt.plot(list(set(novo.ano)),mat[i])
    plt.text(list(set(novo.ano))[-1]-4, mat[i][-1], str(muns[i]), fontsize = 10)
  else:
    plt.plot(list(set(novo.ano)),mat[i])
    plt.text(list(set(novo.ano))[-1], mat[i][-1], str(muns[i]), fontsize = 10)
plt.ylabel("Deforestation (Km^2)",fontsize = 20)
plt.show()
```



As shown above the counties: São Félix do Xingu, Altamira and Pindaré,. Are the ones with a upward tendency for deforestation from the lasts years. Some others (Paragominas, Arinos,Imperatriz, etc) reached a plateau. But none of them reached a downward tendency yet.

Predicting Future Deforestation

Lets now use a Machine learning Algorithm to estimate the total states deforestation for 2022 and 2023. But first we need to make our traind set X from the previous dataset

```
estd = list(Counter(df["estados"]))
mat = []
for i in range(len(estd)):

   data = df[df["estados"] == estd[i]]
   mat.append(stats_year(data,"desmatado",False)[0])

ano = []
est = []
for estado in estd:
  for i in range(2000,2022):
    ano.append(i)
    est.append(estado)


d = {}
d["ano"] = ano
d["estado"] = est
d["desmatado"] = np.array(mat).reshape(1,-1)[0]

X = pd.DataFrame(d)
labels = list(Counter(X["estado"]))

X["estado"] = LabelEncoder().fit_transform(X["estado"])
Y = X.pop("desmatado")
labels_encod = list(Counter(X["estado"]))
```

Model

The model that I choose was a ensemble model with three models KNeighborsRegressor, SGDRegressor and BaggingRegressor. According to the big numbers law this three models mixied will result a more precision than use them separately.

```
scaler = StandardScaler()
scaler.fit(X)
X = scaler.transform(X)
```

Fine tune Hyperparameters

Before we train our ensembe lets tune separately hyperparameters to the three models using GridSearchCV and then use VotingRegressor to train the model.

```
KN = KNeighborsRegressor()
bag = BaggingRegressor()

mod = GridSearchCV(estimator=KN,param_grid= {'n_neighbors':[1,2,3,4,5,6,7,8,9,10]},cv=2)

mod2 = GridSearchCV(estimator=bag,param_grid= {'n_estimators':[100,120,130,150,180]},cv=2)

mod3 = GridSearchCV(estimator=SGDRegressor(max_iter=1200,early_stopping=True),param_grid={'penalty':["l1","l2"]} ,cv=2)

vot = VotingRegressor(estimators=[("kn",mod),("bag",mod2),("est",mod3)])
```

```
X_train,X_test,y_train,y_test=train_test_split(X,Y,test_size=0.1,random_state=True)
```

```
vot.fit(X_train,y_train)
y_pred = vot.predict(X_test)
metrics.r2_score(y_test,y_pred)
```

```
0.8915152717911808
```

Thus our R^2 is close to 0.89 which isn't bad considerig the training set size. Now lets predict the future states deforestation to 2022 and 2023.

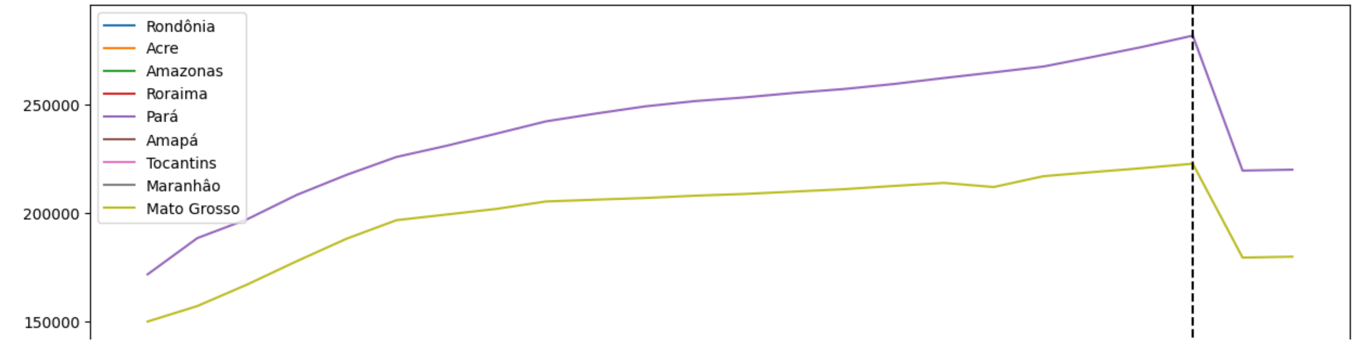
```
m = []
for i in labels_encod:
  for year in range(2022,2024):
      m.append([year,i])
pred = scaler.transform(m)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but StandardScaler wa
  warnings.warn(
```

```
predic = vot.predict(pred)
```

```
Df = pd.DataFrame(d)
ano = [i for i in range(2000,2024)]
```

```
plt.figure(figsize=(15,8))
c = 0
for i in labels:
  dat = Df[Df["estado"] == i]
  es = list(dat["desmatado"])
  es.append(predic[c])
  es.append(predic[c+1])
  plt.plot(ano,es,label = i)
  c+=2
plt.axvline(2021, color='k', linestyle='--')
plt.legend()
plt.xticks(ano, rotation=45)
plt.show()
```



Final Conclusions

From the finds shown previously we can conclude that.

1. Amazon deforestation is currently in a high trend
2. The Counties São Félix do Xingu, Altamira and Pindaré have one of the highest deforestation rates, currently.
3. The states Pará and Mato Grosso have one of the highest deforestation rates, currently.

Analysis and Performance of Regression Model

This present work combined three distinct datasets to analyze the deforestation rate in the Amazon region from the years 2000 to 2020.

After data preparation, the author used hyperparameters to calculate the best model with the aim of predicting the deforestation rate for the years 2022 and 2023.

As a method of error analysis, only the R^2 calculation was used.

We propose performing calculations for other error metrics to better evaluate the generated model.

R^2 The R^2 calculates the percentage of variance that could be predicted by the regression model, that is, how "close" the actual measurements are to our model.

The R^2 is inherently biased because, depending on the optimizer, it may use data correlation to erroneously increase the R^2 value. It can only be applied perfectly to models with only one input and does not respond well to overfitting.

R^2 O R^2 calcula qual a porcentagem da variança que pôde ser prevista pelo modelo de regressão, ou seja, o quão "próximo" as medidas reais estão do nosso modelo.

O R^2 é por padrão enviesado, pois, dependendo do otimizador, pode utilizar a correlação dos dados para incrementar erroneamente o valor de R^2. Só pode ser aplicada perfeitamente em modelos com apenas uma entrada e não responde bem ao Overfitting.

```
print("R² = ", metrics.r2_score(y_test,vot.predict(X_test)))
```

```
R² =  0.8915152717911808
```

Adjusted R^2

It is a more versatile and unbiased alternative measure compared to R^2. It also aims to represent the percentage of variance that a regression model possesses. However, it takes into account how much a feature contributes to the model.

The formula for Adjusted R^2 can be written as:

$R^2a = 1 - ((1-R^2)*(N-1))/N-p-1$

where N is the number of samples,p is the number of features (input data of the model).

Unlike R^2, Adjusted R^2 can be used with more precision and confidence. It can be applied to models with more than one input variable and does not exhibit bias.

```
def adjusted_r2(y_test, y_pred,X_train):
  adj_r2 = (1 - ((1 - metrics.r2_score(y_test, y_pred)) * (len(y_test) - 1)) /
          (len(y_test) - X_train.shape[1] - 1))

  return adj_r2

print("R² Ajustado = ", adjusted_r2(y_test, y_pred, X_train))
```

```
R² Ajustado =  0.8787523625901433
```

Mean Squared Error (MSE)

It is calculated based on the average of the squared errors of predictions. The higher the MSE value, the worse the model.

It is useful when the problem domain does not tolerate large errors, as predictions that are far from the actual values significantly increase the measure's value. However, as it is a metric squared, it is challenging to interpret.

```
MSE = metrics.mean_squared_error(y_test, y_pred)
print("MSE = ", MSE)
```

```
MSE =  666139389.4579426
```

Root Mean Squared Error (RMSE)

Similar to adjusted R^2, RMSE also aims to improve the interpretability of the metric by matching the unit of the data. To achieve this, the square root of MSE is taken.

```
RMSE = np.sqrt(MSE)
print("RMSE = ", RMSE)
```

```
RMSE =  25809.676275729274
```

Mean Absolute Error (MAE)

It is the average of the distances between predicted and actual values. Since it does not square the values, it is not recommended for sensitive problems. However, it is a robust metric for models that need to predict many data points or seasonal data.

MAE does not readily identify outliers like MSE and RMSE, but its interpretation is more intuitive because it is in the same unit as the values being analyzed.

```
MAE = metrics.mean_absolute_error(y_test,y_pred)
print("MAE = ", MAE)
```

```
MAE =  19663.161770228882
```

Mean Absolute Percentage Error (MAPE)

In contrast to other metrics, MAPE expresses a percentage obtained by dividing the difference between the predicted y value and the actual y value by the actual y value.

As it is a percentage, it is easy to understand, but it may not perform as well with values that have a very wide possible range.

```
MAPE = np.mean(np.abs((y_test - y_pred) / y_test)) * 100

print("MAPE = ", MAPE)
```

```
MAPE =  118.10274014302311
```

Root Mean Squared Logarithmic Error (RMSLE)

This error indicator is similar to RMSE, but it uses logarithms to avoid penalizing large differences between the predicted and actual values when both values are very large.

```
RMSLE = metrics.mean_squared_log_error(y_test,y_pred)
print("RMSLE = ", RMSLE)
```

```
RMSLE =  0.6236277930267647
```

Final Considerations

Considering what was covered in class and the study of various types of metrics for error calculation in regression models, it is evident that determining the best formula for this calculation is a complex task.

Among all the tested metrics, R^2 and Adjusted R^2 seem to have easily understandable values and indicate that the model has good predictive behavior.

On the other hand, MSE, RMSE, and MAE presented values that are difficult to interpret, even though RMSE and MAE are in the same unit as the prediction. Their results suggest that the model is performing poorly.

MAPE and RMSLE, which provide values in percentage terms, also indicate that the model is not well-trained, with MAPE showing a 107% error and RMSLE showing a 56% error.

Based on the obtained data and the difficulty of understanding some of the algorithms for error evaluation, I maintain the author's opinion, suggesting R^2 or Adjusted R^2 as metrics for the model.