SQL and Machine learning Task

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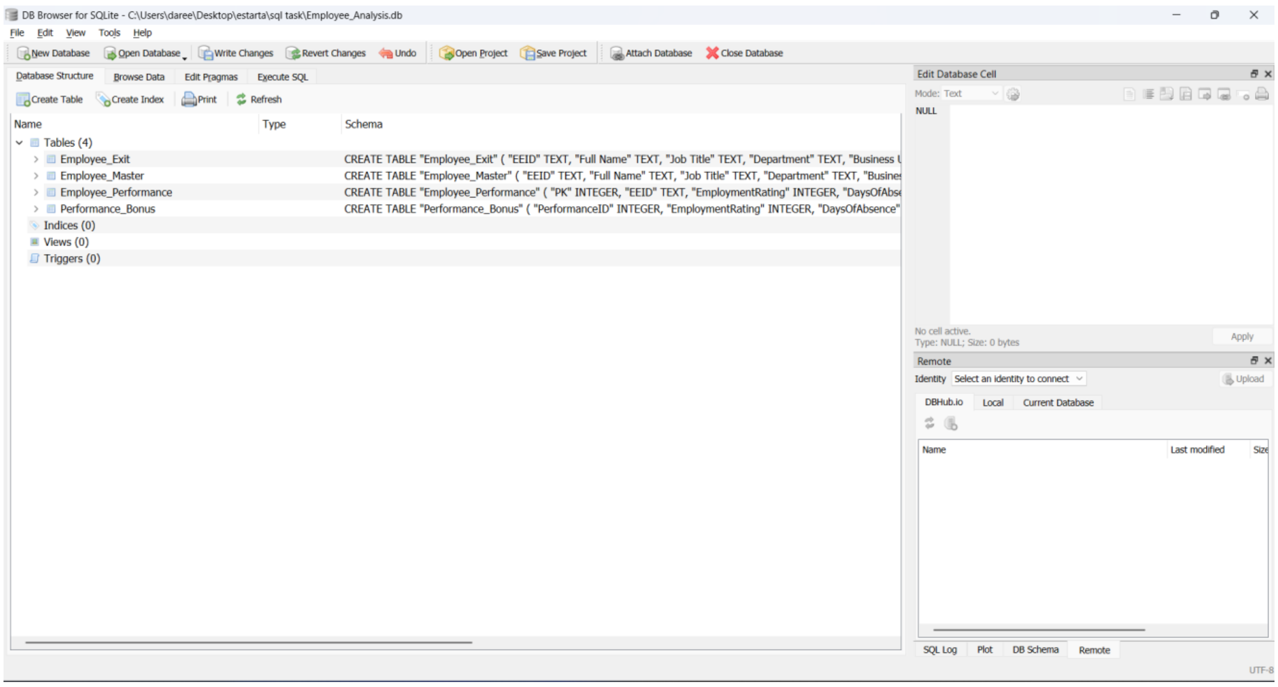
Part A: SQL:

1. Load the data:

I used sqlite as my database and sqlite browser as the interface:

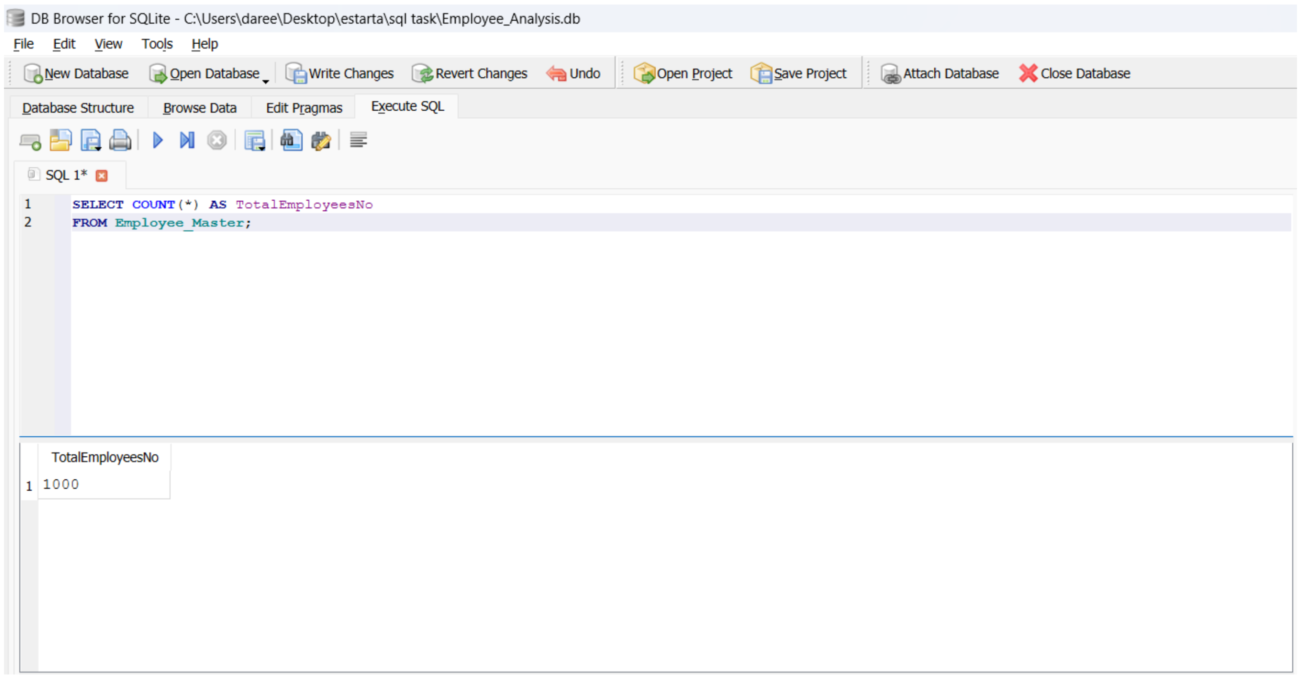


Name	Type	Schema
Tables (4)		
Employee_Exit		CREATE TABLE "Employee_Exit" ("EEID" TEXT, "Full Name" TEXT, "Job Title" TEXT, "Department" TEXT, "Business
Employee_Master		CREATE TABLE "Employee_Master" ("EEID" TEXT, "Full Name" TEXT, "Job Title" TEXT, "Department" TEXT, "Busine
Employee_Performance		CREATE TABLE "Employee_Performance" ("PK" INTEGER, "EEID" TEXT, "EmploymentRating" INTEGER, "DaysOfAbs
Performance_Bonus		CREATE TABLE "Performance_Bonus" ("PerformanceID" INTEGER, "EmploymentRating" INTEGER, "DaysOfAbsence"
Indices (0)		
Views (0)		
Triggers (0)		

Figure 1: load data

2. Know your data:

a. Count total rows in employee:
TotalEmployeesNo = 1000



```sql
SELECT COUNT(*) AS TotalEmployeesNo
FROM Employee_Master;
```

```
  TotalEmployeesNo
1 1000
```

Figure 2: total employees no.

b. Count rows per Department:
I have found that 2 employees are not listed for a department and the highest number of employees are under the IT department

```
SELECT Department, COUNT(*) AS EmployeesCount
FROM Employee_Master
GROUP BY Department
ORDER BY EmployeesCount;
```

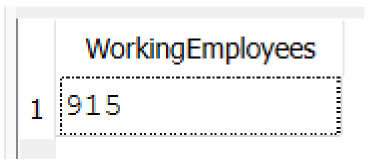
Table 1: rows count per dept

	2
Accounting	96
Finance	120
Marketing	120
Human Resources	124
Sales	140
Engineering	158
IT	240

c. Count how many nulls appear in ExitDate:
I found 915 null record that means that 915 employees are still working

```
SELECT COUNT(*) AS ActiveEmployees
FROM Employee_Master
WHERE "Exit Date" IS NULL;
```

Table 2: null count in exitdate

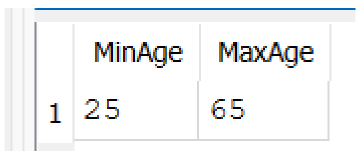


	WorkingEmployees
1	915

d. Age range of employees:

```
SELECT MIN(Age) AS MinAge, MAX(Age) AS MaxAge FROM
Employee_Master;
```

Table 3: age range

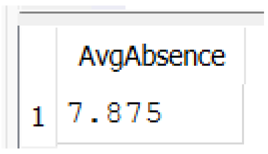


	MinAge	MaxAge
1	25	65

e. Days of Absence:

```
SELECT AVG(DaysOfAbsence) AS AvgAbsence FROM
Employee_Performance;
```

Table 4: avg absence



	AvgAbsence
1	7.875

3. Merge tables:

```
CREATE TABLE Employee_Profile AS
SELECT

table1.*,table2.EmploymentRating,table2.DaysOfAbsence,table2.EducationLevel,
table2.CertificationsEarned
FROM
   Employee_Master AS table1
INNER JOIN
   Employee_Performance AS table2 ON table1.EEID = table2.EEID;
```

- Here I have found that there is multiple duplicated EEID in both tables so I dropped from the employee_master duplicates and kept first occurrence and kept the highest rating from employee_preformance

4. Insert sample records:

```
INSERT INTO Employee_Profile (EEID, "Full Name", "Job Title", Department, Gender,
Age, "Annual Salary", "Bonus %", Country, City, "Exit Date", EmploymentRating,
DaysOfAbsence, EducationLevel, CertificationsEarned)
VALUES
('E1001', 'Dareen Fawwaz', 'Senior Developer', 'IT', 'Female', 20, 135000.00, 0.20,
'Jordan', 'Amman', NULL, 5, 2, 'Master', 3);
INSERT INTO Employee_Profile (EEID, "Full Name", "Job Title", Department, Gender,
Age, "Annual Salary", "Bonus %", Country, City, "Exit Date", EmploymentRating,
DaysOfAbsence, EducationLevel, CertificationsEarned)
VALUES
('E1002', 'Ahmad Ahmad', 'Financial Analyst', 'Finance', 'Male', 27, 85000.00, 0.08,
'Canada', 'Toronto', NULL, 3, 7, 'Bachelor', 1);
INSERT INTO Employee_Profile (EEID, "Full Name", "Job Title", Department, Gender,
Age, "Annual Salary", "Bonus %", Country, City, "Exit Date", EmploymentRating,
DaysOfAbsence, EducationLevel, CertificationsEarned)
VALUES
```

```
('E1003', 'Mohammad Mohammad', 'HR Assistant', 'HR', 'Male', 23, 55000.00, 0.00,
'USA', 'Phoenix', NULL, 3, 10, 'Associate', 0);
INSERT INTO Employee_Profile (EEID, "Full Name", "Job Title", Department, Gender,
Age, "Annual Salary", "Bonus %", Country, City, "Exit Date", EmploymentRating,
DaysOfAbsence, EducationLevel, CertificationsEarned)
VALUES
('E1004', 'Sara Ahmad', 'IT Support Specialist', 'IT', 'Female', 45, 95000.00, 0.10, 'USA',
'Phoenix', NULL, 4, 4, 'Master', 2);
INSERT INTO Employee_Profile (EEID, "Full Name", "Job Title", Department, Gender,
Age, "Annual Salary", "Bonus %", Country, City, "Exit Date", EmploymentRating,
DaysOfAbsence, EducationLevel, CertificationsEarned)
VALUES
('E1005', 'Maria Rami', 'Marketing Specialist', 'Marketing', 'Female', 30, 70000.00, 0.05,
'Mexico', 'Mexico City', NULL, 2, 20, 'Bachelor', 1);
INSERT INTO Employee_Profile (EEID, "Full Name", "Job Title", Department, Gender,
Age, "Annual Salary", "Bonus %", Country, City, "Exit Date", EmploymentRating,
DaysOfAbsence, EducationLevel, CertificationsEarned)
VALUES
('E1006', 'Dalia Ahmad', 'Sales Director', 'Sales', 'Male', 52, 160000.00, 0.30, 'UK',
'London', NULL, 4, 3, 'Master', 3);
INSERT INTO Employee_Profile (EEID, "Full Name", "Job Title", Department, Gender,
Age, "Annual Salary", "Bonus %", Country, City, "Exit Date", EmploymentRating,
DaysOfAbsence, EducationLevel, CertificationsEarned)
VALUES
('E1007', 'Tala Mohammad', 'Data Scientist', 'IT', 'Female', 29, 110000.00, 0.15,
'Germany', 'Berlin', '2025-01-15', 5, 0, 'PhD', 2);
INSERT INTO Employee_Profile (EEID, "Full Name", "Job Title", Department, Gender,
Age, "Annual Salary", "Bonus %", Country, City, "Exit Date", EmploymentRating,
DaysOfAbsence, EducationLevel, CertificationsEarned)
VALUES
('E1008', 'Rami Ahmad', 'Logistics Coordinator', 'Operations', 'Male', 48, 65000.00, 0.00,
'USA', 'Dallas', NULL, 3, 15, 'Bachelor', 1);
INSERT INTO Employee_Profile (EEID, "Full Name", "Job Title", Department, Gender,
Age, "Annual Salary", "Bonus %", Country, City, "Exit Date", EmploymentRating,
DaysOfAbsence, EducationLevel, CertificationsEarned)
VALUES
('E1009', 'Lina Rami', 'Treasury Manager', 'Finance', 'Female', 38, 105000.00, 0.12,
'France', 'Paris', NULL, 4, 6, 'Master', 0);
INSERT INTO Employee_Profile (EEID, "Full Name", "Job Title", Department, Gender,
Age, "Annual Salary", "Bonus %", Country, City, "Exit Date", EmploymentRating,
DaysOfAbsence, EducationLevel, CertificationsEarned)
VALUES
('E1010', 'Alia Ahmad', 'Junior DevOps', 'IT', 'Male', 24, 68000.00, 0.05, 'USA', 'Phoenix',
NULL, 4, 5, 'Bachelor', 1);
```

5. Conditional update:

```
UPDATE Employee_Profile
SET City = 'Abu Dhabi'
WHERE
   City = 'Phoenix'
   AND Gender = 'Male'
   AND Department = 'IT';
```

Table 5: city equal "Abu Dhabi"

E00523	Daniel Jordan	Network Administrator	IT	Corporate	Male	Caucasian	58	7/26/1993	$69,260	0	United States	Abu Dhabi		8	15	Bachelor's	3
E01722	Asher Huynh	Manager	IT	Manufacturing	Male	Asian	45	1/22/2015	$101,288	0.1	United States	Abu Dhabi		10	9	Bachelor's	4
E1010	Alia Ahmad	Junior DevOps	IT		Male		24		68000.0	0.05	USA	Abu Dhabi		4	5	Bachelor	1

6. Export CSVs:

First check departments in table the result is equal 10 departments:

```
SELECT DISTINCT Department FROM Employee_Profile;
```

Table 6: departments

IT
Finance
Sales
Accounting
Human Resources
Engineering
Marketing
NULL
HR
Operations

then I proceeded with this query for every department and exported it into an CSV file and merged the HR and Human Resources and filled the null department with "Unassigned":

```
SELECT * FROM Employee_Profile WHERE Department = 'IT';
```

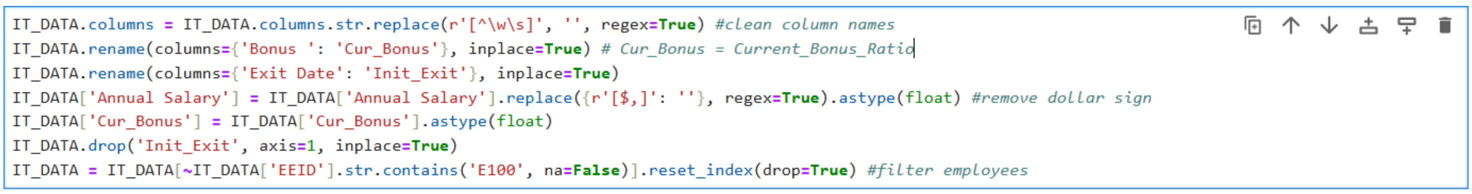
Part B: Python And ML:

1. Prepare the IT dataset:

- I imported these libraries to help with machine learning build:

```
import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler, OneHotEncoder

from sklearn.compose import ColumnTransformer

from sklearn.pipeline import Pipeline

from sklearn.linear_model import LinearRegression

from sklearn.metrics import mean_absolute_error, mean_squared_error

from datetime import datetime

import re
```

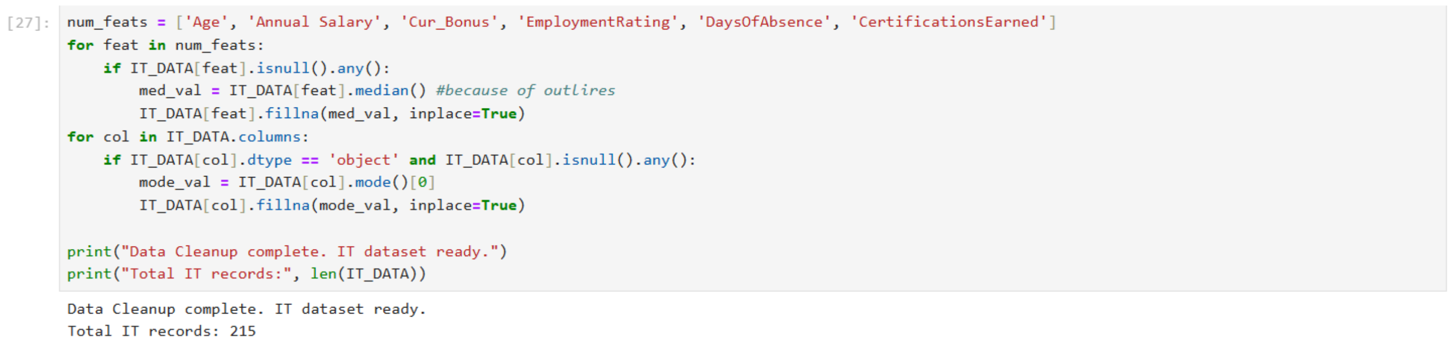
- Clean data and drop exit column:



```
IT_DATA.columns = IT_DATA.columns.str.replace(r'[^\w\s]', '', regex=True) #clean column names
IT_DATA.rename(columns={'Bonus ': 'Cur_Bonus'}, inplace=True) # Cur_Bonus = Current_Bonus_Ratio
IT_DATA.rename(columns={'Exit Date': 'Init_Exit'}, inplace=True)
IT_DATA['Annual Salary'] = IT_DATA['Annual Salary'].replace({r'[$,]': ''}, regex=True).astype(float) #remove dollar sign
IT_DATA['Cur_Bonus'] = IT_DATA['Cur_Bonus'].astype(float)
IT_DATA.drop('Init_Exit', axis=1, inplace=True)
IT_DATA = IT_DATA[~IT_DATA['EEID'].str.contains('E100', na=False)].reset_index(drop=True) #filter employees
```

Figure 3: code 1

- Clean the columns names
- Renamed the bonus column to cur_bonus (current) and exit data to init_exit
- Removed the dollar sign from anuual salary column
- Changed bonus datatype into float
- Dropped the exit date column
- Filtered the employees by EEID



```
[27]: num_feats = ['Age', 'Annual Salary', 'Cur_Bonus', 'EmploymentRating', 'DaysOfAbsence', 'CertificationsEarned']
      for feat in num_feats:
          if IT_DATA[feat].isnull().any():
              med_val = IT_DATA[feat].median() #because of outlires
              IT_DATA[feat].fillna(med_val, inplace=True)
      for col in IT_DATA.columns:
          if IT_DATA[col].dtype == 'object' and IT_DATA[col].isnull().any():
              mode_val = IT_DATA[col].mode()[0]
              IT_DATA[col].fillna(mode_val, inplace=True)

      print("Data Cleanup complete. IT dataset ready.")
      print("Total IT records:", len(IT_DATA))

      Data Cleanup complete. IT dataset ready.
      Total IT records: 215
```

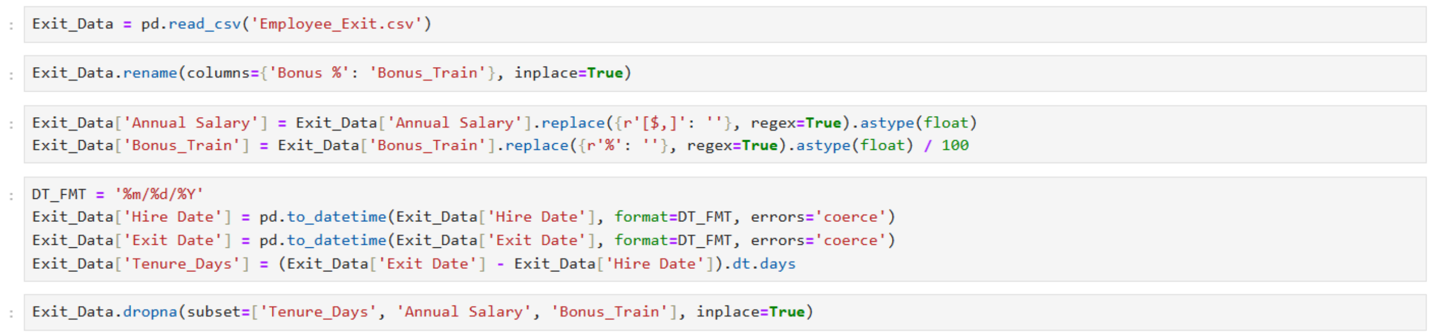
Figure 4: code 2

- Filled numerical columns with median to avoid outliers

- Filled object data type columns with mode value

2. Exit-Date Prediction:

- Load and clean data:



```
Exit_Data = pd.read_csv('Employee_Exit.csv')
```

```
Exit_Data.rename(columns={'Bonus %': 'Bonus_Train'}, inplace=True)
```

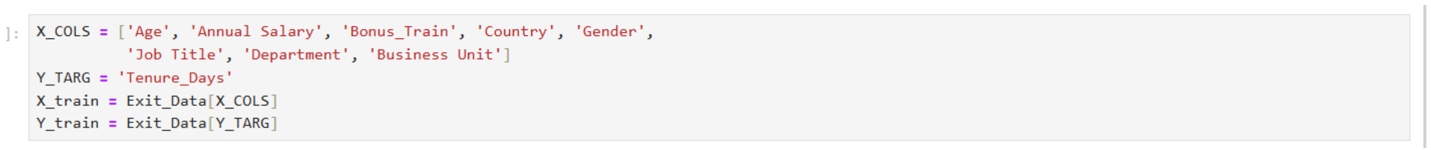
```
Exit_Data['Annual Salary'] = Exit_Data['Annual Salary'].replace({r'[$,]': ''}, regex=True).astype(float)
Exit_Data['Bonus_Train'] = Exit_Data['Bonus_Train'].replace({r'%': ''}, regex=True).astype(float) / 100
```

```
DT_FMT = '%m/%d/%Y'
Exit_Data['Hire Date'] = pd.to_datetime(Exit_Data['Hire Date'], format=DT_FMT, errors='coerce')
Exit_Data['Exit Date'] = pd.to_datetime(Exit_Data['Exit Date'], format=DT_FMT, errors='coerce')
Exit_Data['Tenure_Days'] = (Exit_Data['Exit Date'] - Exit_Data['Hire Date']).dt.days
```

```
Exit_Data.dropna(subset=['Tenure_Days', 'Annual Salary', 'Bonus_Train'], inplace=True)
```

Figure 5: code 3

- Removed dollar sign from annual salary and % sign from bonus
- Renamed bonus to bonus_train
- Reformatted the hire date and exit date into date format
- Added a column that calculates the difference between hire date and exit date
- Dropped null and nan values from features columns



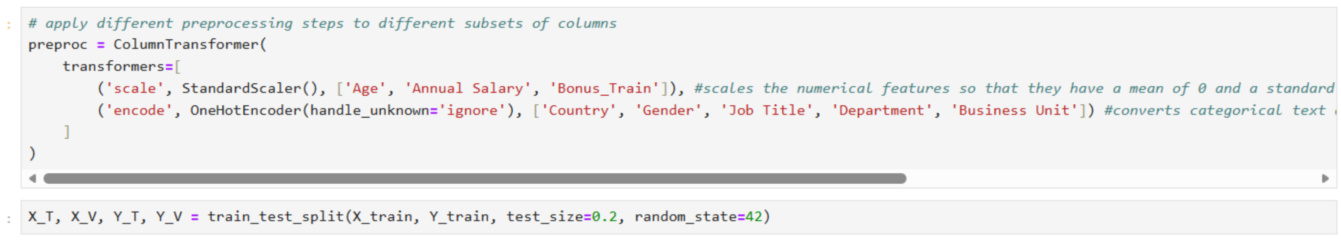
```
X_COLS = ['Age', 'Annual Salary', 'Bonus_Train', 'Country', 'Gender',
          'Job Title', 'Department', 'Business Unit']
Y_TARG = 'Tenure_Days'
X_train = Exit_Data[X_COLS]
Y_train = Exit_Data[Y_TARG]
```

Figure 6: code 4

- The chosen features are:

X_COLS = ['Age', 'Annual Salary', 'Bonus_Train', 'Country', 'Gender', 'Job Title', 'Department', 'Business Unit']

- And the target variable is tenure_days(difference between hire and exit dates)

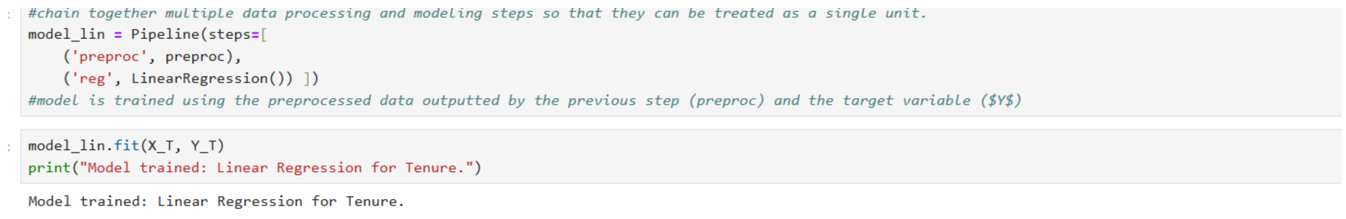


```python
# apply different preprocessing steps to different subsets of columns
preproc = ColumnTransformer(
    transformers=[
        ('scale', StandardScaler(), ['Age', 'Annual Salary', 'Bonus_Train']), #scales the numerical features so that they have a mean of 0 and a standard
        ('encode', OneHotEncoder(handle_unknown='ignore'), ['Country', 'Gender', 'Job Title', 'Department', 'Business Unit']) #converts categorical text
    ]
)
```

```python
X_T, X_V, Y_T, Y_V = train_test_split(X_train, Y_train, test_size=0.2, random_state=42)
```

Figure 7: code 5

- apply different pre-processing steps to different subsets of columns
- scales the numerical features so that they have a mean of 0 and a standard deviation of 1
- converts categorical text data into a numerical format that machine learning models can understand
- then split data into 20% validation and 80% training



```python
#chain together multiple data processing and modeling steps so that they can be treated as a single unit.
model_lin = Pipeline(steps=[
    ('preproc', preproc),
    ('reg', LinearRegression()) ])
#model is trained using the preprocessed data outputted by the previous step (preproc) and the target variable ($Y$)
```

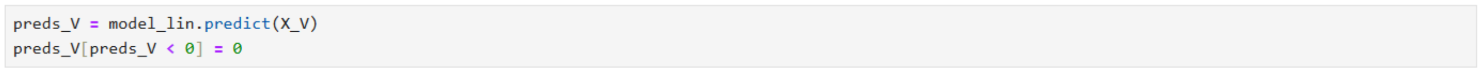
```python
model_lin.fit(X_T, Y_T)
print("Model trained: Linear Regression for Tenure.")
```

```
Model trained: Linear Regression for Tenure.
```

Figure 8: code 6

- chained together multiple data processing and modelling steps so that they can be treated as a single unit

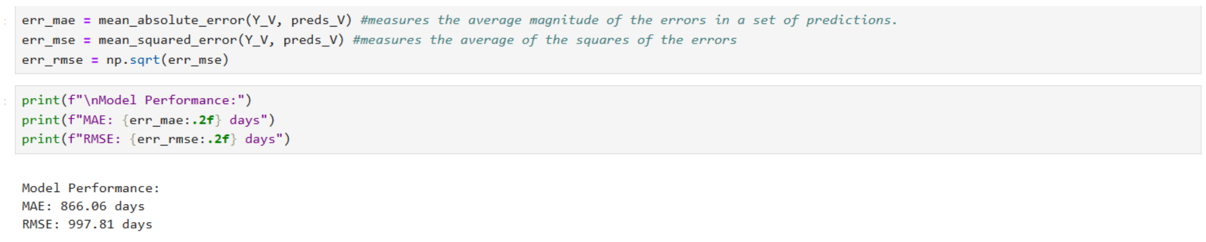
- train data using preproc defined function and linear regression



```python
preds_V = model_lin.predict(X_V)
preds_V[preds_V < 0] = 0
```

Figure 9: code 7

- predict and if any negative prediction set it to zero



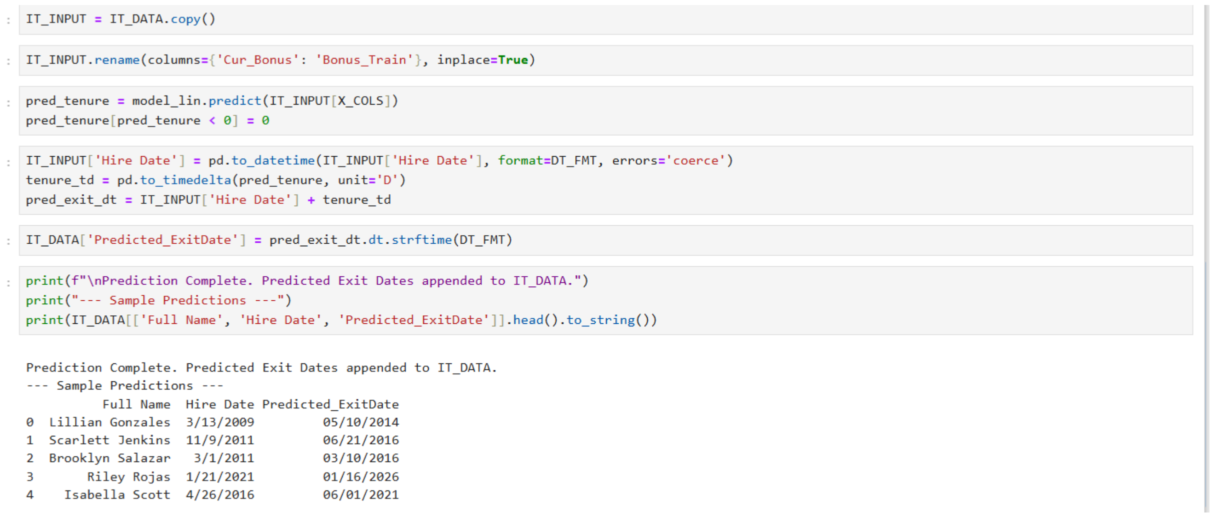
```python
err_mae = mean_absolute_error(Y_V, preds_V) #measures the average magnitude of the errors in a set of predictions.
err_mse = mean_squared_error(Y_V, preds_V) #measures the average of the squares of the errors
err_rmse = np.sqrt(err_mse)
```

```python
print(f"\nModel Performance:")
print(f"MAE: {err_mae:.2f} days")
print(f"RMSE: {err_rmse:.2f} days")
```

```
Model Performance:
MAE: 866.06 days
RMSE: 997.81 days
```

Figure 10: code 8

- calculate the mean absolute error and mean squared error and take the square root of it



```
IT_INPUT = IT_DATA.copy()
```

```
IT_INPUT.rename(columns={'Cur_Bonus': 'Bonus_Train'}, inplace=True)
```

```
pred_tenure = model_lin.predict(IT_INPUT[X_COLS])
pred_tenure[pred_tenure < 0] = 0
```

```
IT_INPUT['Hire Date'] = pd.to_datetime(IT_INPUT['Hire Date'], format=DT_FMT, errors='coerce')
tenure_td = pd.to_timedelta(pred_tenure, unit='D')
pred_exit_dt = IT_INPUT['Hire Date'] + tenure_td
```

```
IT_DATA['Predicted_ExitDate'] = pred_exit_dt.dt.strftime(DT_FMT)
```

```
print(f"\nPrediction Complete. Predicted Exit Dates appended to IT_DATA.")
print("--- Sample Predictions ---")
print(IT_DATA[['Full Name', 'Hire Date', 'Predicted_ExitDate']].head().to_string())
```

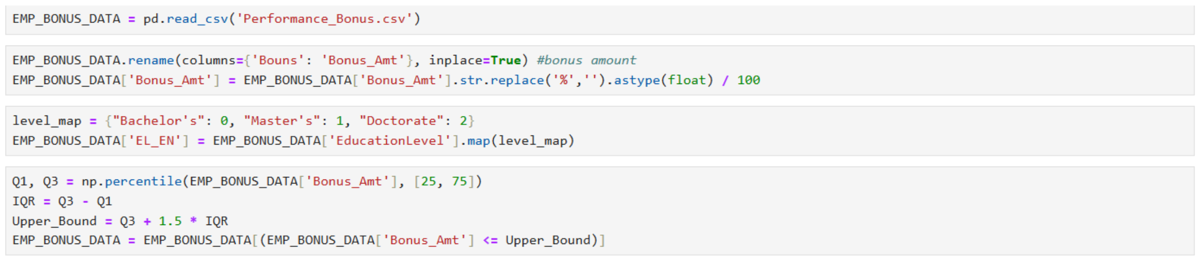
```
Prediction Complete. Predicted Exit Dates appended to IT_DATA.
--- Sample Predictions ---
          Full Name  Hire Date Predicted_ExitDate
0  Lillian Gonzales  3/13/2009         05/10/2014
1  Scarlett Jenkins  11/9/2011         06/21/2016
2  Brooklyn Salazar   3/1/2011         03/10/2016
3       Riley Rojas  1/21/2021         01/16/2026
4    Isabella Scott  4/26/2016         06/01/2021
```

Figure 11: code 9

- Predict exit dates and append them as a new column ExitDate to Employee_Profile _IT

3. Bonus Percentage Prediction:

- Load and clean data:



```
EMP_BONUS_DATA = pd.read_csv('Performance_Bonus.csv')
```

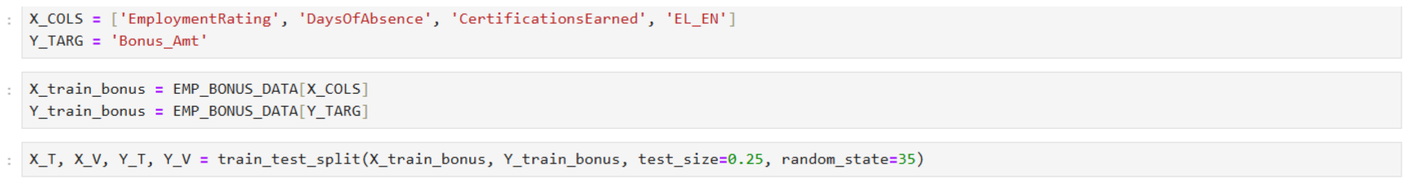
```
EMP_BONUS_DATA.rename(columns={'Bouns': 'Bonus_Amt'}, inplace=True) #bonus amount
EMP_BONUS_DATA['Bonus_Amt'] = EMP_BONUS_DATA['Bonus_Amt'].str.replace('%','').astype(float) / 100
```

```
level_map = {"Bachelor's": 0, "Master's": 1, "Doctorate": 2}
EMP_BONUS_DATA['EL_EN'] = EMP_BONUS_DATA['EducationLevel'].map(level_map)
```

```
Q1, Q3 = np.percentile(EMP_BONUS_DATA['Bonus_Amt'], [25, 75])
IQR = Q3 - Q1
Upper_Bound = Q3 + 1.5 * IQR
EMP_BONUS_DATA = EMP_BONUS_DATA[(EMP_BONUS_DATA['Bonus_Amt'] <= Upper_Bound)]
```

Figure 12: code 10

- Load the preformane_bonus data
- Renamed the bonus into bonus_amt (amount) and removed the dollar sign
- Mapped (encode) the education level into numerical values
- Remove outlies from bonus column



```
X_COLS = ['EmploymentRating', 'DaysOfAbsence', 'CertificationsEarned', 'EL_EN']
Y_TARG = 'Bonus_Amt'
```

```
X_train_bonus = EMP_BONUS_DATA[X_COLS]
Y_train_bonus = EMP_BONUS_DATA[Y_TARG]
```

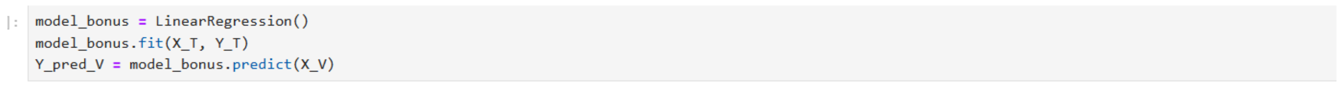
```
X_T, X_V, Y_T, Y_V = train_test_split(X_train_bonus, Y_train_bonus, test_size=0.25, random_state=35)
```

Figure 13: code 11

- the chosen features are:

X_COLS = ['EmploymentRating', 'DaysOfAbsence', 'CertificationsEarned', 'EL_EN']

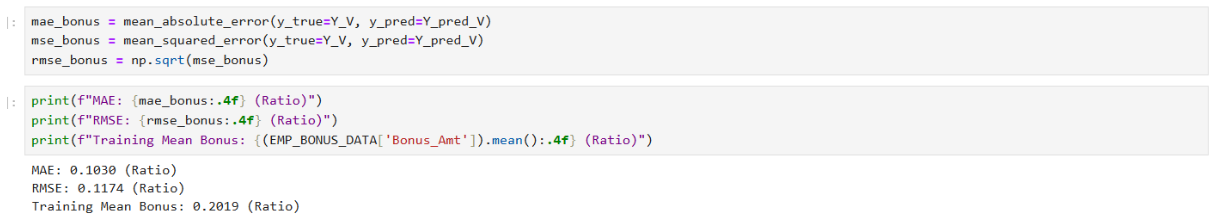
- And the target variable is bonus amount
- Split data into 25% validation and 75% training



```
model_bonus = LinearRegression()
model_bonus.fit(X_T, Y_T)
Y_pred_V = model_bonus.predict(X_V)
```

Figure 14: code 12

- Preform prediction functions



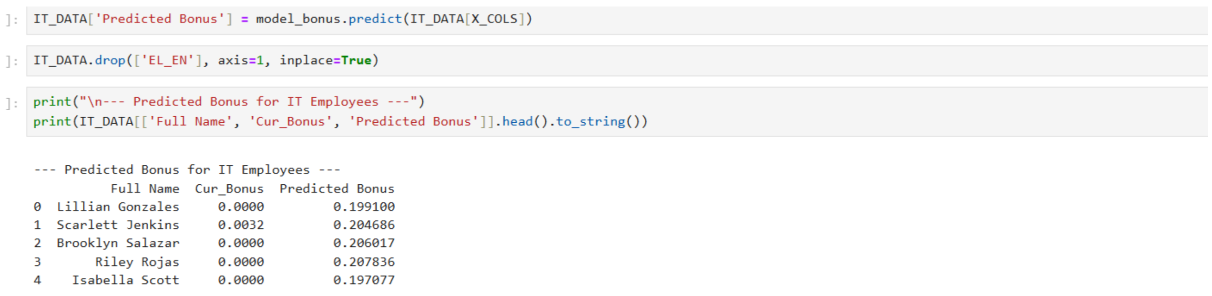
```
mae_bonus = mean_absolute_error(y_true=Y_V, y_pred=Y_pred_V)
mse_bonus = mean_squared_error(y_true=Y_V, y_pred=Y_pred_V)
rmse_bonus = np.sqrt(mse_bonus)
```

```
print(f"MAE: {mae_bonus:.4f} (Ratio)")
print(f"RMSE: {rmse_bonus:.4f} (Ratio)")
print(f"Training Mean Bonus: {(EMP_BONUS_DATA['Bonus_Amt']).mean():.4f} (Ratio)")
```

```
MAE: 0.1030 (Ratio)
RMSE: 0.1174 (Ratio)
Training Mean Bonus: 0.2019 (Ratio)
```

Figure 15: code 13

- calculate mean absolute error and mean squared error



```
IT_DATA['Predicted Bonus'] = model_bonus.predict(IT_DATA[X_COLS])
```

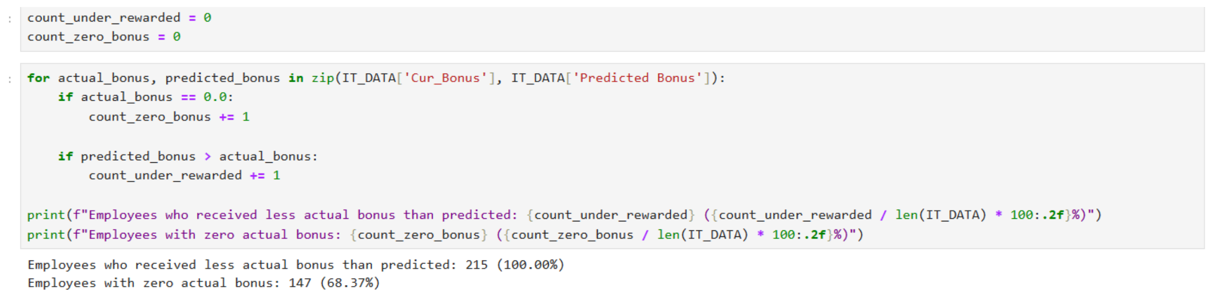
```
IT_DATA.drop(['EL_EN'], axis=1, inplace=True)
```

```
print("\n--- Predicted Bonus for IT Employees ---")
print(IT_DATA[['Full Name', 'Cur_Bonus', 'Predicted Bonus']].head().to_string())
```

```
--- Predicted Bonus for IT Employees ---
          Full Name  Cur_Bonus  Predicted Bonus
0  Lillian Gonzales     0.0000         0.199100
1  Scarlett Jenkins     0.0032         0.204686
2  Brooklyn Salazar     0.0000         0.206017
3       Riley Rojas     0.0000         0.207836
4    Isabella Scott     0.0000         0.197077
```

Figure 16: code 14

- Append predictions in a new column Predicted_bonus to IT dataset



```
count_under_rewarded = 0
count_zero_bonus = 0
```

```
for actual_bonus, predicted_bonus in zip(IT_DATA['Cur_Bonus'], IT_DATA['Predicted Bonus']):
    if actual_bonus == 0.0:
        count_zero_bonus += 1

    if predicted_bonus > actual_bonus:
        count_under_rewarded += 1

print(f"Employees who received less actual bonus than predicted: {count_under_rewarded} ({count_under_rewarded / len(IT_DATA) * 100:.2f}%)")
print(f"Employees with zero actual bonus: {count_zero_bonus} ({count_zero_bonus / len(IT_DATA) * 100:.2f}%)")
```

```
Employees who received less actual bonus than predicted: 215 (100.00%)
Employees with zero actual bonus: 147 (68.37%)
```

Figure 17: code 15

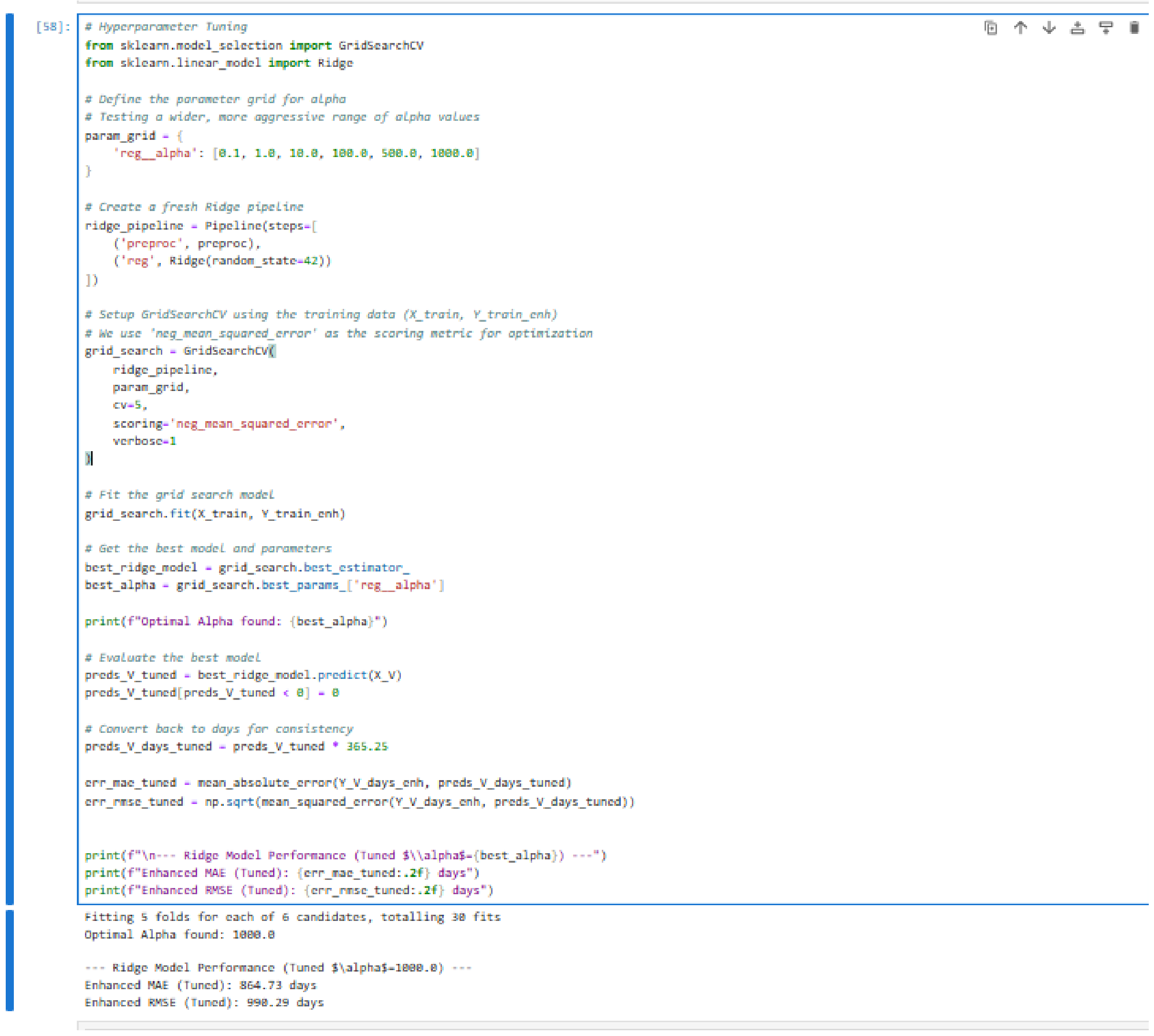
- Employees who received less actual bonus than predicted: 215 (100 .00%)
- Employees with zero actual bonus: 147 (68.37%)
- According to numbers and percentages all employees is predicted to receive a bonus amount greater than what they already have and most employees in original dataset have zero bonuses

Part c: enhancements:

- I applied 2 techniques in each prediction for exit date and bonus amount:

1. Hyperparameter Tuning:

- Exit date prediction:



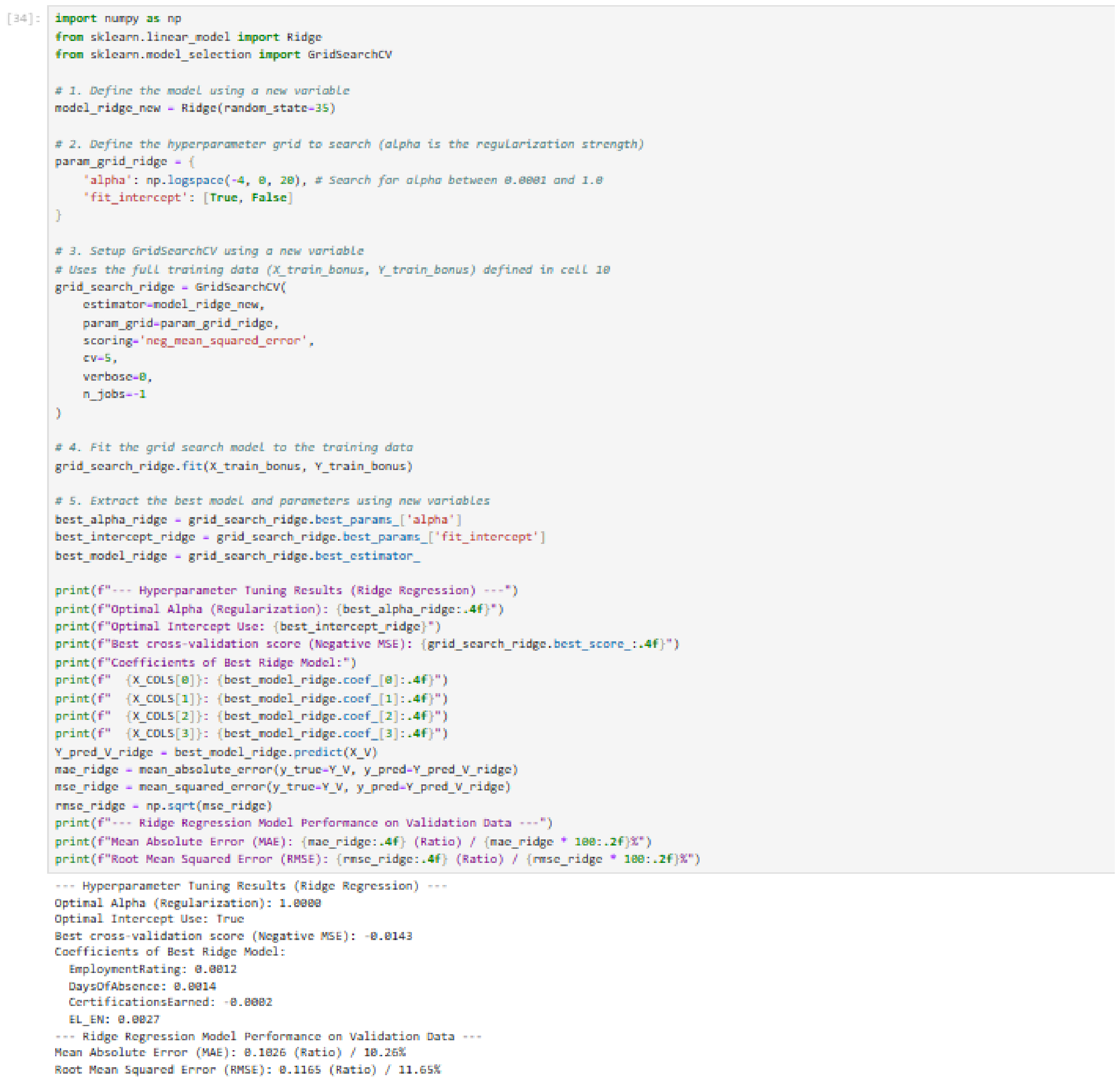
```
[58]: # Hyperparameter Tuning
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Ridge

# Define the parameter grid for alpha
# Testing a wider, more aggressive range of alpha values
param_grid = {
    'reg__alpha': [0.1, 1.0, 10.0, 100.0, 500.0, 1000.0]
}

# Create a fresh Ridge pipeline
ridge_pipeline = Pipeline(steps=[
    ('preproc', preproc),
    ('reg', Ridge(random_state=42))
])

# Setup GridSearchCV using the training data (X_train, Y_train_enh)
# We use 'neg_mean_squared_error' as the scoring metric for optimization
grid_search = GridSearchCV(
    ridge_pipeline,
    param_grid,
    cv=5,
    scoring='neg_mean_squared_error',
    verbose=1
)

# Fit the grid search model
grid_search.fit(X_train, Y_train_enh)

# Get the best model and parameters
best_ridge_model = grid_search.best_estimator_
best_alpha = grid_search.best_params_['reg__alpha']

print(f"Optimal Alpha found: {best_alpha}")

# Evaluate the best model
preds_V_tuned = best_ridge_model.predict(X_V)
preds_V_tuned[preds_V_tuned < 0] = 0

# Convert back to days for consistency
preds_V_days_tuned = preds_V_tuned * 365.25

err_mae_tuned = mean_absolute_error(Y_V_days_enh, preds_V_days_tuned)
err_rmse_tuned = np.sqrt(mean_squared_error(Y_V_days_enh, preds_V_days_tuned))


print(f"\n--- Ridge Model Performance (Tuned $\\alpha$={best_alpha}) ---")
print(f"Enhanced MAE (Tuned): {err_mae_tuned:.2f} days")
print(f"Enhanced RMSE (Tuned): {err_rmse_tuned:.2f} days")
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits
Optimal Alpha found: 1000.0

--- Ridge Model Performance (Tuned $\alpha$=1000.0) ---
Enhanced MAE (Tuned): 864.73 days
Enhanced RMSE (Tuned): 990.29 days
```

Figure 18: code 16

- MAE has decreased by 2 days
- RMSE has decreased by 7 days

- Bonus amount prediction:



```
[34]: import numpy as np
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV

# 1. Define the model using a new variable
model_ridge_new = Ridge(random_state=35)

# 2. Define the hyperparameter grid to search (alpha is the regularization strength)
param_grid_ridge = {
    'alpha': np.logspace(-4, 0, 20), # Search for alpha between 0.0001 and 1.0
    'fit_intercept': [True, False]
}

# 3. Setup GridSearchCV using a new variable
# Uses the full training data (X_train_bonus, Y_train_bonus) defined in cell 10
grid_search_ridge = GridSearchCV(
    estimator=model_ridge_new,
    param_grid=param_grid_ridge,
    scoring='neg_mean_squared_error',
    cv=5,
    verbose=0,
    n_jobs=-1
)

# 4. Fit the grid search model to the training data
grid_search_ridge.fit(X_train_bonus, Y_train_bonus)

# 5. Extract the best model and parameters using new variables
best_alpha_ridge = grid_search_ridge.best_params_['alpha']
best_intercept_ridge = grid_search_ridge.best_params_['fit_intercept']
best_model_ridge = grid_search_ridge.best_estimator_

print(f"--- Hyperparameter Tuning Results (Ridge Regression) ---")
print(f"Optimal Alpha (Regularization): {best_alpha_ridge:.4f}")
print(f"Optimal Intercept Use: {best_intercept_ridge}")
print(f"Best cross-validation score (Negative MSE): {grid_search_ridge.best_score_:.4f}")
print(f"Coefficients of Best Ridge Model:")
print(f"  {X_COLS[0]}: {best_model_ridge.coef_[0]:.4f}")
print(f"  {X_COLS[1]}: {best_model_ridge.coef_[1]:.4f}")
print(f"  {X_COLS[2]}: {best_model_ridge.coef_[2]:.4f}")
print(f"  {X_COLS[3]}: {best_model_ridge.coef_[3]:.4f}")
Y_pred_V_ridge = best_model_ridge.predict(X_V)
mae_ridge = mean_absolute_error(y_true=Y_V, y_pred=Y_pred_V_ridge)
mse_ridge = mean_squared_error(y_true=Y_V, y_pred=Y_pred_V_ridge)
rmse_ridge = np.sqrt(mse_ridge)
print(f"--- Ridge Regression Model Performance on Validation Data ---")
print(f"Mean Absolute Error (MAE): {mae_ridge:.4f} (Ratio) / {mae_ridge * 100:.2f}%")
print(f"Root Mean Squared Error (RMSE): {rmse_ridge:.4f} (Ratio) / {rmse_ridge * 100:.2f}%")
```

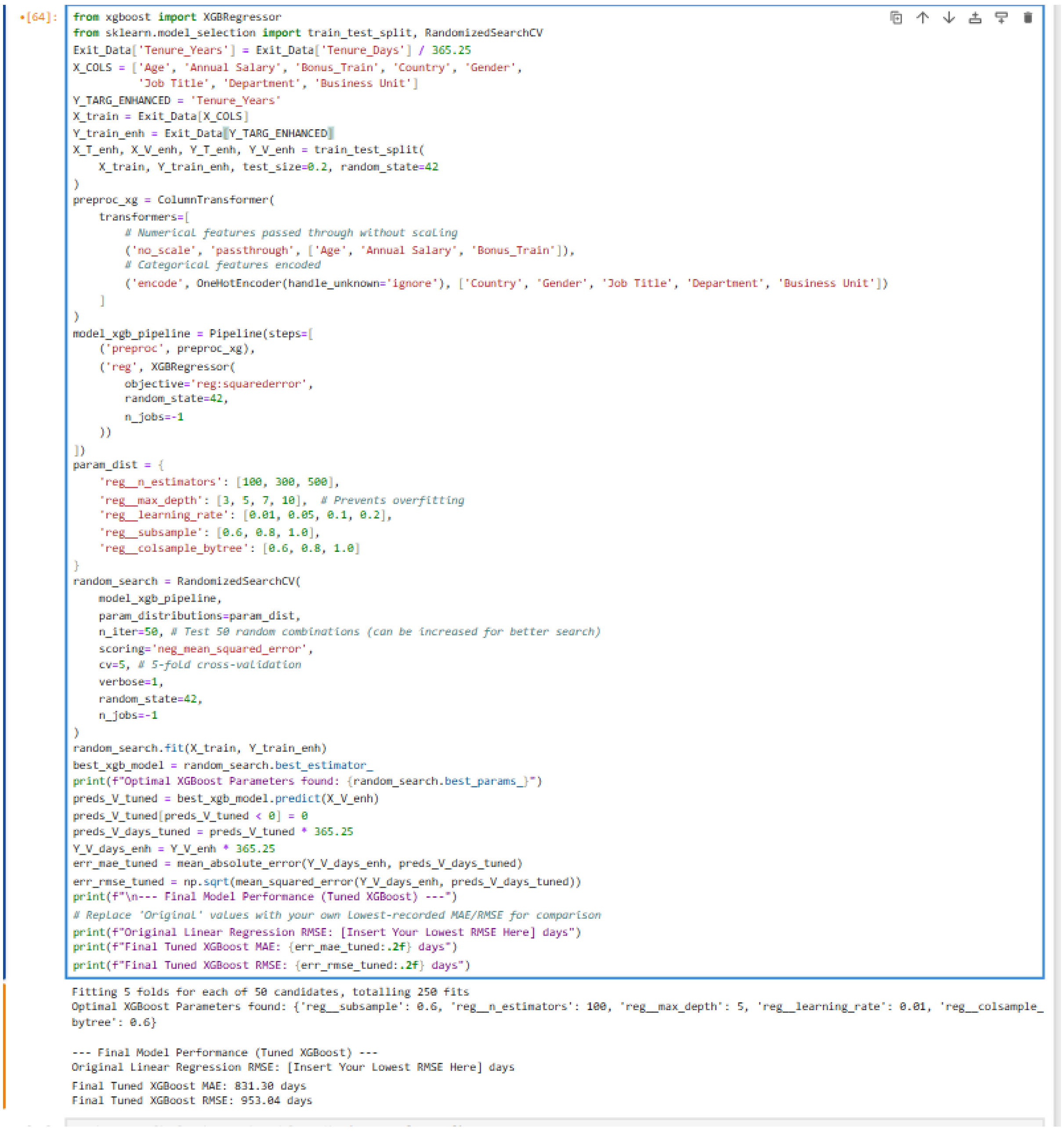
```
--- Hyperparameter Tuning Results (Ridge Regression) ---
Optimal Alpha (Regularization): 1.0000
Optimal Intercept Use: True
Best cross-validation score (Negative MSE): -0.0143
Coefficients of Best Ridge Model:
  EmploymentRating: 0.0012
  DaysOfAbsence: 0.0014
  CertificationsEarned: -0.0002
  EL_EN: 0.0027
--- Ridge Regression Model Performance on Validation Data ---
Mean Absolute Error (MAE): 0.1026 (Ratio) / 10.26%
Root Mean Squared Error (RMSE): 0.1165 (Ratio) / 11.65%
```

Figure 19: code 17

- MAE has decreased by 0.04%
- RMSE has decreased by 0.09%

2. Tuned XGBoost Implementation:

- Exit date prediction:



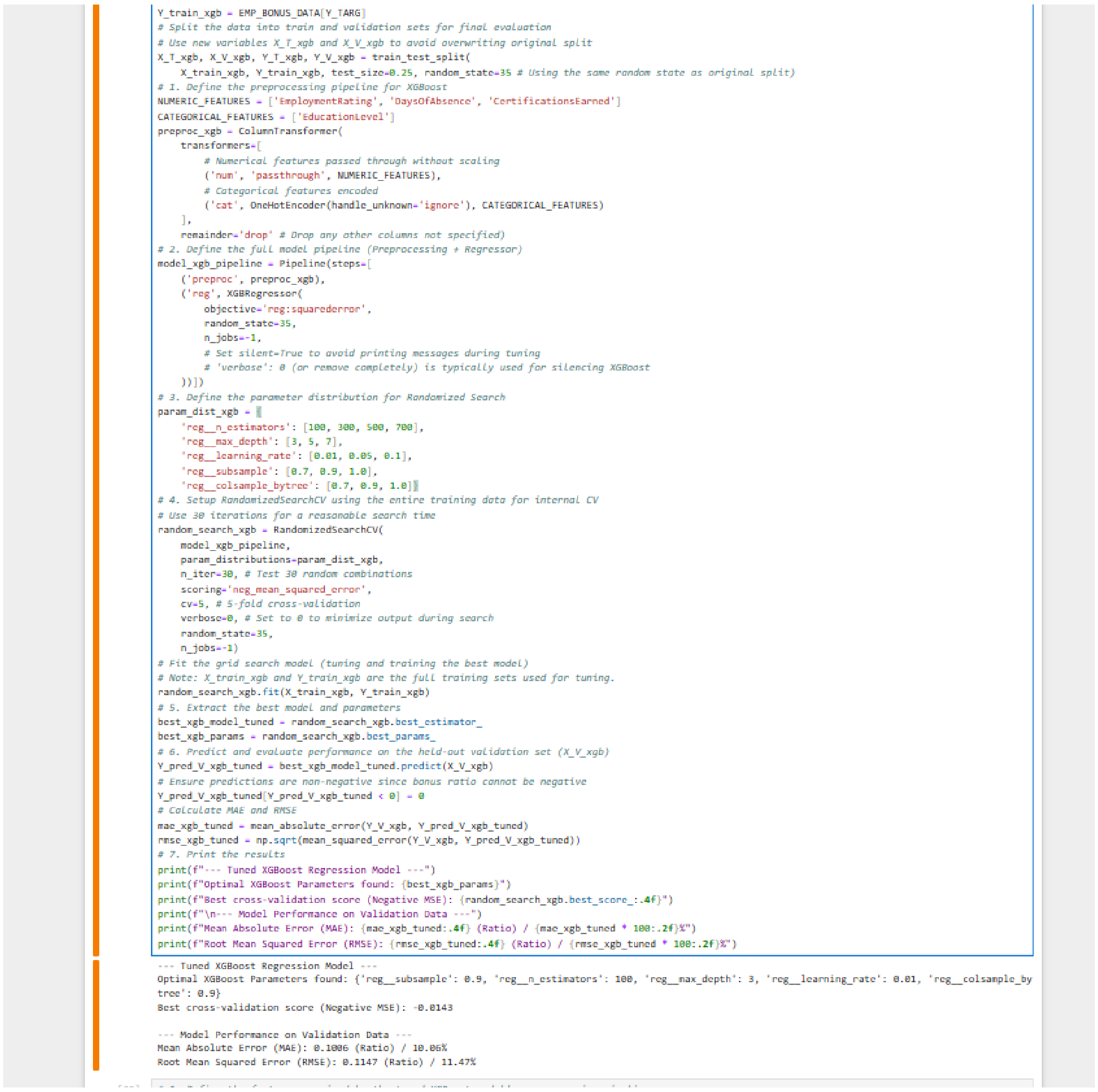
```
[64]:
from xgboost import XGBRegressor
from sklearn.model_selection import train_test_split, RandomizedSearchCV
Exit_Data['Tenure_Years'] = Exit_Data['Tenure_Days'] / 365.25
X_COLS = ['Age', 'Annual Salary', 'Bonus_Train', 'Country', 'Gender',
          'Job Title', 'Department', 'Business Unit']
Y_TARG_ENHANCED = 'Tenure_Years'
X_train = Exit_Data[X_COLS]
Y_train_enh = Exit_Data[Y_TARG_ENHANCED]
X_T_enh, X_V_enh, Y_T_enh, Y_V_enh = train_test_split(
    X_train, Y_train_enh, test_size=0.2, random_state=42
)
preproc_xg = ColumnTransformer(
    transformers=[
        # Numerical features passed through without scaling
        ('no_scale', 'passthrough', ['Age', 'Annual Salary', 'Bonus_Train']),
        # Categorical features encoded
        ('encode', OneHotEncoder(handle_unknown='ignore'), ['Country', 'Gender', 'Job Title', 'Department', 'Business Unit'])
    ]
)
model_xgb_pipeline = Pipeline(steps=[
    ('preproc', preproc_xg),
    ('reg', XGBRegressor(
        objective='reg:squarederror',
        random_state=42,
        n_jobs=-1
    ))
])
param_dist = {
    'reg__n_estimators': [100, 300, 500],
    'reg__max_depth': [3, 5, 7, 10],  # Prevents overfitting
    'reg__learning_rate': [0.01, 0.05, 0.1, 0.2],
    'reg__subsample': [0.6, 0.8, 1.0],
    'reg__colsample_bytree': [0.6, 0.8, 1.0]
}
random_search = RandomizedSearchCV(
    model_xgb_pipeline,
    param_distributions=param_dist,
    n_iter=50, # Test 50 random combinations (can be increased for better search)
    scoring='neg_mean_squared_error',
    cv=5, # 5-fold cross-validation
    verbose=1,
    random_state=42,
    n_jobs=-1
)
random_search.fit(X_train, Y_train_enh)
best_xgb_model = random_search.best_estimator_
print(f"Optimal XGBoost Parameters found: {random_search.best_params_}")
preds_V_tuned = best_xgb_model.predict(X_V_enh)
preds_V_tuned[preds_V_tuned < 0] = 0
preds_V_days_tuned = preds_V_tuned * 365.25
Y_V_days_enh = Y_V_enh * 365.25
err_mae_tuned = mean_absolute_error(Y_V_days_enh, preds_V_days_tuned)
err_rmse_tuned = np.sqrt(mean_squared_error(Y_V_days_enh, preds_V_days_tuned))
print(f"\n--- Final Model Performance (Tuned XGBoost) ---")
# Replace 'Original' values with your own Lowest-recorded MAE/RMSE for comparison
print(f"Original Linear Regression RMSE: [Insert Your Lowest RMSE Here] days")
print(f"Final Tuned XGBoost MAE: {err_mae_tuned:.2f} days")
print(f"Final Tuned XGBoost RMSE: {err_rmse_tuned:.2f} days")
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
Optimal XGBoost Parameters found: {'reg__subsample': 0.6, 'reg__n_estimators': 100, 'reg__max_depth': 5, 'reg__learning_rate': 0.01, 'reg__colsample_
bytree': 0.6}

--- Final Model Performance (Tuned XGBoost) ---
Original Linear Regression RMSE: [Insert Your Lowest RMSE Here] days
Final Tuned XGBoost MAE: 831.30 days
Final Tuned XGBoost RMSE: 953.04 days
```

Figure 20: code 18

- MAE has decreased by 35 days
- RMSE has decreased by 44 days

- Bonus amount prediction:



```
Y_train_xgb = EMP_BONUS_DATA[Y_TARG]
# Split the data into train and validation sets for final evaluation
# Use new variables X_T_xgb and X_V_xgb to avoid overwriting original split
X_T_xgb, X_V_xgb, Y_T_xgb, Y_V_xgb = train_test_split(
    X_train_xgb, Y_train_xgb, test_size=0.25, random_state=35 # Using the same random state as original split)
# 1. Define the preprocessing pipeline for XGBoost
NUMERIC_FEATURES = ['EmploymentRating', 'DaysOfAbsence', 'CertificationsEarned']
CATEGORICAL_FEATURES = ['EducationLevel']
preproc_xgb = ColumnTransformer(
    transformers=[
        # Numerical features passed through without scaling
        ('num', 'passthrough', NUMERIC_FEATURES),
        # Categorical features encoded
        ('cat', OneHotEncoder(handle_unknown='ignore'), CATEGORICAL_FEATURES)
    ],
    remainder='drop' # Drop any other columns not specified)
# 2. Define the full model pipeline (Preprocessing + Regressor)
model_xgb_pipeline = Pipeline(steps=[
    ('preproc', preproc_xgb),
    ('reg', XGBRegressor(
        objective='reg:squarederror',
        random_state=35,
        n_jobs=-1,
        # Set silent=True to avoid printing messages during tuning
        # 'verbose': 0 (or remove completely) is typically used for silencing XGBoost
    ))])
# 3. Define the parameter distribution for Randomized Search
param_dist_xgb = {
    'reg__n_estimators': [100, 300, 500, 700],
    'reg__max_depth': [3, 5, 7],
    'reg__learning_rate': [0.01, 0.05, 0.1],
    'reg__subsample': [0.7, 0.9, 1.0],
    'reg__colsample_bytree': [0.7, 0.9, 1.0]}
# 4. Setup RandomizedSearchCV using the entire training data for internal CV
# Use 30 iterations for a reasonable search time
random_search_xgb = RandomizedSearchCV(
    model_xgb_pipeline,
    param_distributions=param_dist_xgb,
    n_iter=30, # Test 30 random combinations
    scoring='neg_mean_squared_error',
    cv=5, # 5-fold cross-validation
    verbose=0, # Set to 0 to minimize output during search
    random_state=35,
    n_jobs=-1)
# Fit the grid search model (tuning and training the best model)
# Note: X_train_xgb and Y_train_xgb are the full training sets used for tuning.
random_search_xgb.fit(X_train_xgb, Y_train_xgb)
# 5. Extract the best model and parameters
best_xgb_model_tuned = random_search_xgb.best_estimator_
best_xgb_params = random_search_xgb.best_params_
# 6. Predict and evaluate performance on the held-out validation set (X_V_xgb)
Y_pred_V_xgb_tuned = best_xgb_model_tuned.predict(X_V_xgb)
# Ensure predictions are non-negative since bonus ratio cannot be negative
Y_pred_V_xgb_tuned[Y_pred_V_xgb_tuned < 0] = 0
# Calculate MAE and RMSE
mae_xgb_tuned = mean_absolute_error(Y_V_xgb, Y_pred_V_xgb_tuned)
rmse_xgb_tuned = np.sqrt(mean_squared_error(Y_V_xgb, Y_pred_V_xgb_tuned))
# 7. Print the results
print(f"--- Tuned XGBoost Regression Model ---")
print(f"Optimal XGBoost Parameters found: {best_xgb_params}")
print(f"Best cross-validation score (Negative MSE): {random_search_xgb.best_score_:.4f}")
print(f"\n--- Model Performance on Validation Data ---")
print(f"Mean Absolute Error (MAE): {mae_xgb_tuned:.4f} (Ratio) / {mae_xgb_tuned * 100:.2f}%")
print(f"Root Mean Squared Error (RMSE): {rmse_xgb_tuned:.4f} (Ratio) / {rmse_xgb_tuned * 100:.2f}%")
```

```
--- Tuned XGBoost Regression Model ---
Optimal XGBoost Parameters found: {'reg__subsample': 0.9, 'reg__n_estimators': 100, 'reg__max_depth': 3, 'reg__learning_rate': 0.01, 'reg__colsample_by
tree': 0.9}
Best cross-validation score (Negative MSE): -0.0143

--- Model Performance on Validation Data ---
Mean Absolute Error (MAE): 0.1006 (Ratio) / 10.06%
Root Mean Squared Error (RMSE): 0.1147 (Ratio) / 11.47%
```

Figure 21: code 19

- MAE has decreased by 0.30%
- RMSE has decreased by 0.27%

3. Results:

- I implemented the XGBoost technique due to the numbers are better using it and predicted the values of IT_DATA using it to generate files with the predicted values of bonus amount and exit date