Imports

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LinearRegression, LogisticRegression,Ridge
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error, accuracy_s
from sklearn.preprocessing import StandardScaler,OneHotEncoder,LabelEncoder
from sklearn.feature_selection import RFE
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn.ensemble import RandomForestRegressor
```

Regression

Data reading for regression

```
#dataset read
dataset = pd.read_csv('/content/drive/MyDrive/secondYear/5CS037 - Concepts and Technolog
df = pd.DataFrame(dataset)
```

```
print("Dataset Info:")
print(df.info())
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  53940 non-null  int64
 1   carat       53940 non-null  float64
 2   cut         53940 non-null  object
 3   color       53940 non-null  object
 4   clarity     53940 non-null  object
 5   depth       53940 non-null  float64
 6   table       53940 non-null  float64
 7   price       53940 non-null  int64
 8   x           53940 non-null  float64
 9   y           53940 non-null  float64
 10  z           53940 non-null  float64
dtypes: float64(6), int64(2), object(3)
```

```
memory usage: 4.5+ MB
None
```

```
# printing few dataset

df.head(10)
```

	Unnamed: 0	carat	cut	color	clarity	depth	table	price	x	y	z
0	1	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	2	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	3	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	4	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	5	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75
5	6	0.24	Very Good	J	VVS2	62.8	57.0	336	3.94	3.96	2.48
6	7	0.24	Very Good	I	VVS1	62.3	57.0	336	3.95	3.98	2.47
7	8	0.26	Very	H	SI1	61.9	55.0	337	4.07	4.11	2.53

Next steps: Generate code with df View recommended plots New interactive sheet

Data cleaning

```
df = df.dropna()
print("\nMissing Values:")
print(df.isnull().sum())

print("\nNumber of duplicate rows:", df.duplicated().sum())
df = df.drop_duplicates()
print("Number of rows after removing duplicates:", len(df))
```

```
Missing Values:
Unnamed: 0    0
carat         0
cut           0
color         0
clarity       0
depth         0
table         0
price         0
x             0
y             0
z             0
dtype: int64
```

```
Number of duplicate rows: 0
Number of rows after removing duplicates: 53940
```

Statistics

```
summary_stats = df['price'].describe()
print(summary_stats)
```

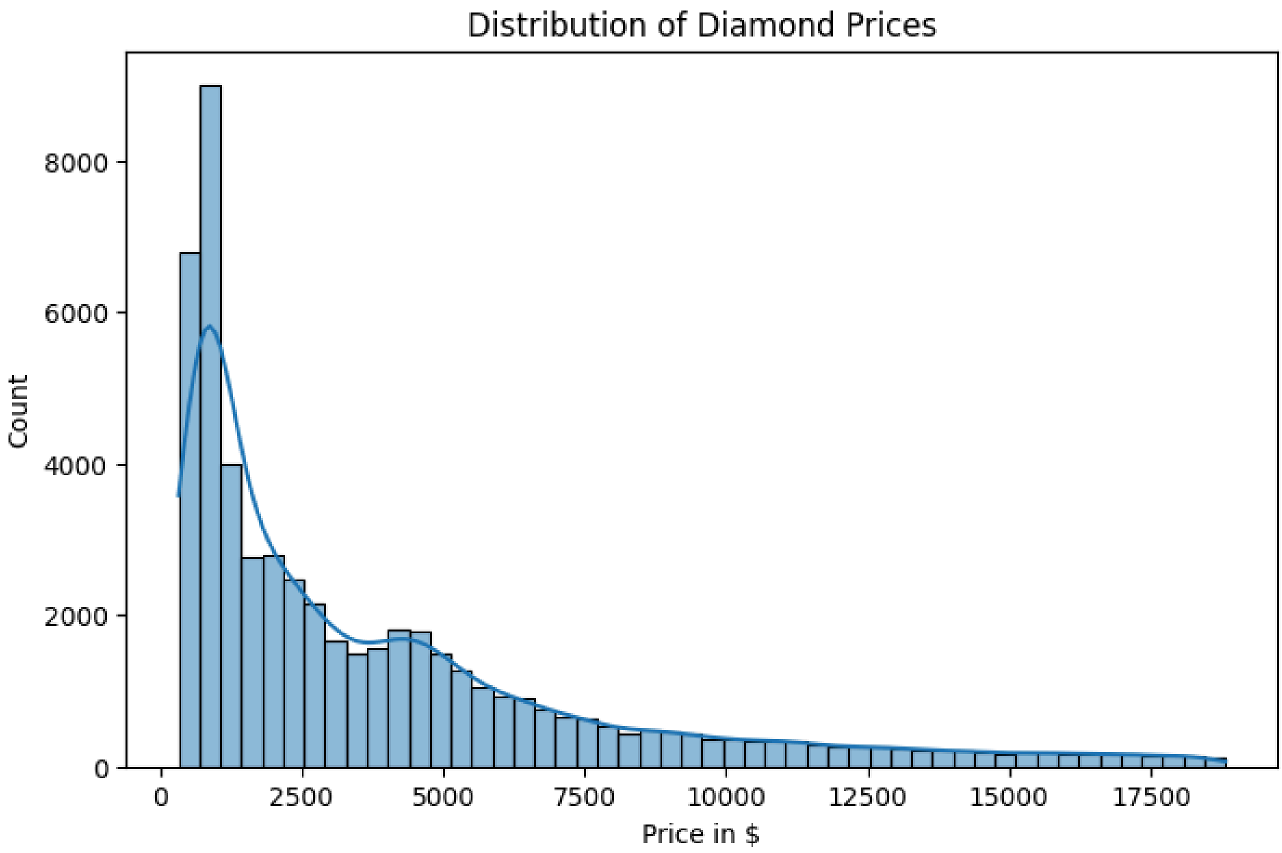
```
count    53940.000000
mean      3932.799722
std       3989.439738
min        326.000000
25%        950.000000
50%       2401.000000
75%       5324.250000
max      18823.000000
Name: price, dtype: float64
```

```
correlation = df['price'].corr(df['carat'])
print(f"Correlation between Price and Carat: {correlation:.2f}")
```

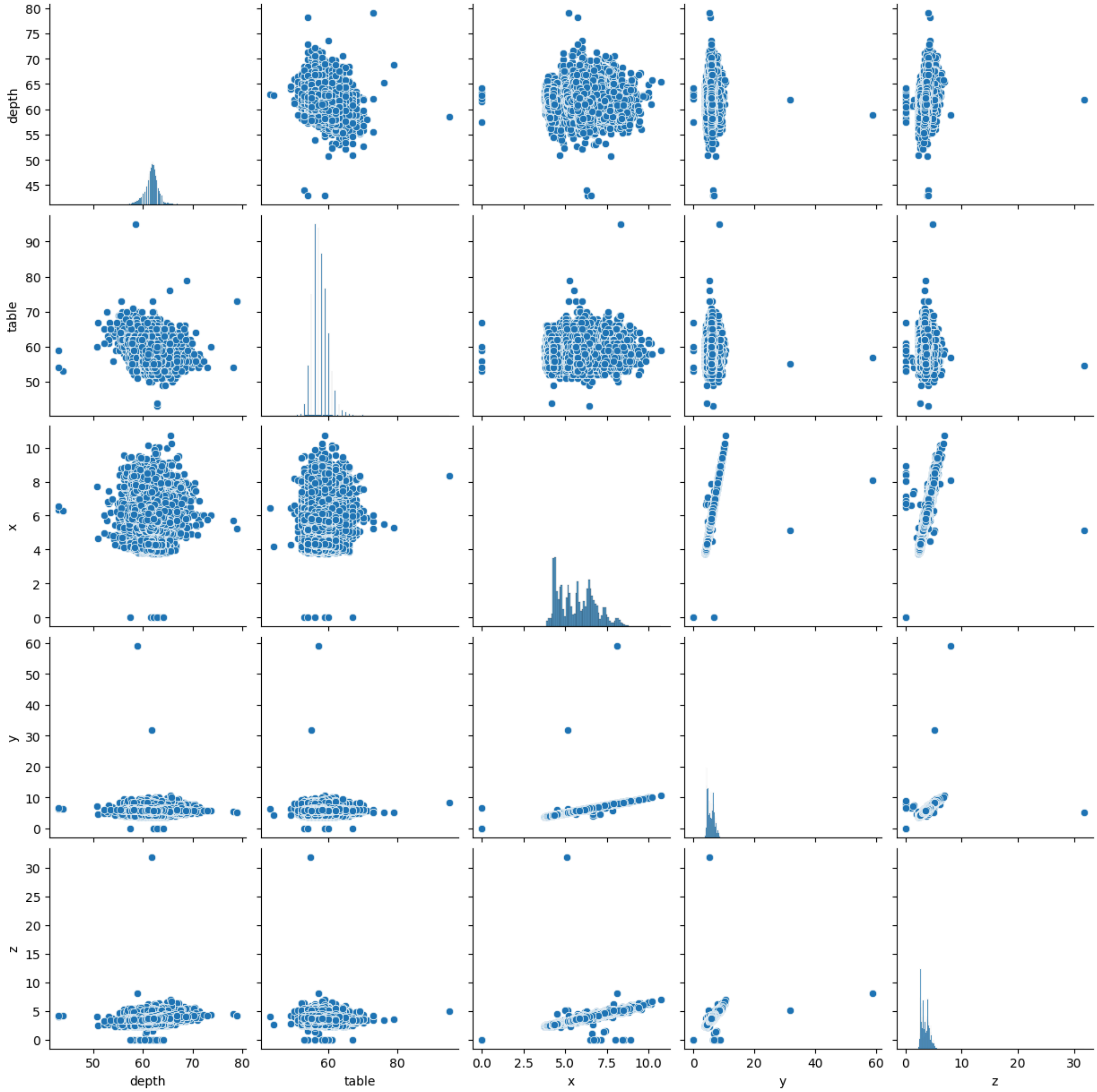
```
Correlation between Price and Carat: 0.92
```

Data Visualization

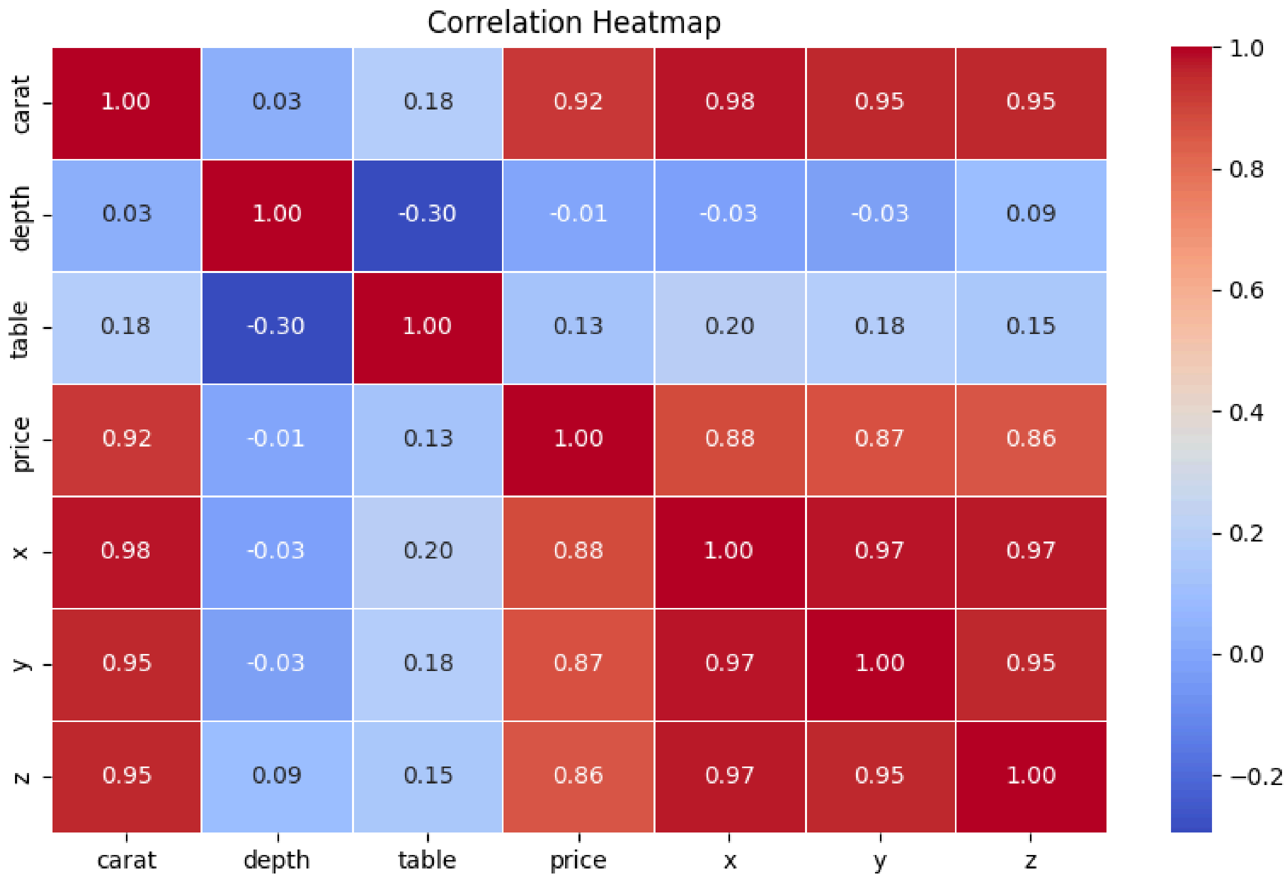
```
plt.figure(figsize=(8, 5))
sns.histplot(df["price"], bins=50, kde=True)
plt.title("Distribution of Diamond Prices")
plt.xlabel("Price in $")
plt.show()
```




```
sns.pairplot(df[["depth", "table", "x", "y","z"]])
plt.show()
```




```
numeric_df = df.select_dtypes(include=['number']).iloc[:, 1:]
correlation_matrix = numeric_df.corr()
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.5)
plt.title("Correlation Heatmap ")
plt.show()
```



Data separation

```
X = df.drop(columns=["price"])
y = df["price"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Add a bias term (column of ones) to the features matrix
X_train = np.hstack((np.ones((X_train.shape[0], 1)), X_train))
X_test = np.hstack((np.ones((X_test.shape[0], 1)), X_test))

# Initialize weights to 0
weights = np.zeros(X_train.shape[1])
```

Model From Scratch

```
def compute_cost(X, Y, W):
    """ Parameters:
    This function finds the Mean Square Error.
    Input parameters:
      X: Feature Matrix
      Y: Target Matrix
```

```
      W: Weight Matrix
    Output Parameters:
      J: accumulated mean square error.
    """
    # Number of samples
    m = X.shape[0]
    #predicted values(Y_pred = np.matmul(X,W))
    Y_pred = np.matmul(X, W)
    # Compute the squared errors
    squared_errors = (Y_pred - Y) ** 2
    return (1 / (2 * m)) * np.sum(squared_errors)

# Gradient Descent Function
def gradient_descent(X, Y, W, alpha, iterations):
    cost_history = []
    m = len(Y)

    for iteration in range(iterations):
        # Hypothesis Values
        Y_pred = np.matmul(X, W)
        # Difference b/w Hypothesis and Actual Y
        loss = Y_pred - Y
        dw = (1 / m) * np.matmul(X.T, loss)  # Gradient calculation
        W = W - alpha * dw  # Weight update

        # New Cost Value
        cost = compute_cost(X, Y, W)
        cost_history.append(cost)

    return W, cost_history

# RMSE Calculation
def rmse(Y_true, Y_pred):
    return np.sqrt(np.mean((Y_true - Y_pred) ** 2))

# R-squared Calculation
def r2(Y_true, Y_pred):
    # np.mean(Y_true) = mean of y true
    ss_total = np.sum((Y_true - np.mean(Y_true)) ** 2)
    ss_residual = np.sum((Y_true - Y_pred) ** 2)
    return 1 - (ss_residual / ss_total)

# Train-Test Split Function
def train_test_split_scratch(X, y, test_size=0.2, random_seed=42):
    """
    Splits dataset into train and test sets.

    Arguments:
    X : np.ndarray
        Feature matrix.
    y : np.ndarray
        Target array.
    test_size : float
        Proportion of the dataset to include in the test split (0 < test_size < 1).
    random_seed : int
        Seed for reproducibility.
```

```
    Returns:
    X_train, X_test, y_train, y_test : np.ndarray
        Training and testing splits of features and target.
    """
    np.random.seed(random_seed)
    indices = np.arange(X.shape[0])
    np.random.shuffle(indices)
    test_size = int(len(X) * test_size)
    test_indices, train_indices = indices[:test_size], indices[test_size:]
    return X[train_indices], X[test_indices], y[train_indices], y[test_indices]

def main():
    # Load Dataset
    # Label Encoding for Categorical Columns
    label_encoder = LabelEncoder()
    categorical_columns = []


    # Define Features and Target
    feature_cols = []
    X = df[feature_cols].values
    Y = df['price'].values.reshape(-1, 1)  # Convert to column vector

    mean_X = np.mean(X, axis=0)
    std_X = np.std(X, axis=0)
    X = (X - mean_X) / (std_X + 1e-8)

    X = np.c_[np.ones(X.shape[0]), X]

    X_train, X_test, Y_train, Y_test = train_test_split_scratch(X, Y, test_size=0.2, ranc

    W = np.zeros((X_train.shape[1], 1))

    # Hyperparameters
    alpha = 0.01  # Learning Rate
    iterations = 1000  # Number of Iterations

    # Train the Model using Gradient Descent
    W_optimal, cost_history = gradient_descent(X_train, Y_train, W, alpha, iterations)

    # Make Predictions
    Y_pred = np.dot(X_test, W_optimal)

    # Evaluate Model
    model_rmse = rmse(Y_test, Y_pred)
    model_r2 = r2(Y_test, Y_pred)

    # Output Results
    print("Final Weights (including bias):", W_optimal.flatten())
    print("Cost History (First 10 iterations):", cost_history[:10])
    print("RMSE on Test Set:", model_rmse)
    print("R-Squared on Test Set:", model_r2)

# Execute the main function
if __name__ == "__main__":
```

```
    main()
```

```
Final Weights (including bias): [3939.32063454]
Cost History (First 10 iterations): [15565242.99733858, 15413896.062194156, 15265560.
RMSE on Test Set: 3987.220752951641
R-Squared on Test Set: -6.969201434570138e-05
```

Primary Model

```
from sklearn.model_selection import train_test_split


X = df.drop(columns=['price']).values
y = df['price'].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)
```

```
X_train shape: (43152, 10)
X_test shape: (10788, 10)
y_train shape: (43152,)
y_test shape: (10788,)
```

```
numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns.tolist()
categorical_cols = df.select_dtypes(include=['object']).columns.tolist()

numerical_cols.remove('price')

encoder = OneHotEncoder(drop='first', sparse_output=False)
encoded_categorical = encoder.fit_transform(df[categorical_cols])
encoded_categorical_df = pd.DataFrame(encoded_categorical, columns=encoder.get_feature_na

scaler = StandardScaler()
scaled_numerical = scaler.fit_transform(df[numerical_cols])
scaled_numerical_df = pd.DataFrame(scaled_numerical, columns=numerical_cols)

X = pd.concat([scaled_numerical_df, encoded_categorical_df], axis=1)
X.insert(0, 'Intercept', 1)

y = df['price'].values.reshape(-1, 1)

X_np = X.values
y_np = y

X_train, X_test, y_train, y_test = train_test_split(X_np, y_np, test_size=0.3, random_sta
```

```
ridge = Ridge(alpha=0.1)
ridge.fit(X_train, y_train)

y_pred = ridge.predict(X_test)

rmse_library = np.sqrt(np.mean((y_test - y_pred) ** 2))

mse_library = np.mean((y_test - y_pred) ** 2)

mae_library = np.mean(np.abs(y_test - y_pred))

r2_library = ridge.score(X_test, y_test)

print(f"RMSE: {rmse_library}")
print(f"MSE: {mse_library}")
print(f"MAE: {mae_library}")
print(f"R² Score: {r2_library}")
```

```
RMSE: 5469.985955759538
MSE: 29920746.35620659
MAE: 4013.3260353062324
R² Score: 0.9206226715690513
```

```
linear_reg_model = LinearRegression()
linear_reg_model.fit(X_train, y_train)

y_pred_linear = linear_reg_model.predict(X_test)
y_traina = y_train.ravel()
random_forest_model = RandomForestRegressor(random_state=42)
random_forest_model.fit(X_train, y_train)

y_pred_rf = random_forest_model.predict(X_test)

print("Linear Regression:")
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred_linear))
print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred_linear))
print("R-squared (R2):", r2_score(y_test, y_pred_linear))
print("\nRandom Forest Regression:")
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred_rf))
print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred_rf))
print("R-squared (R2):", r2_score(y_test, y_pred_rf))
```

```
al/lib/python3.11/dist-packages/sklearn/base.py:1389: DataConversionWarning: A column
 fit_method(estimator, *args, **kwargs)
egression:
ared Error (MSE): 1238015.3387700708
olute Error (MAE): 734.0152467397219
d (R2): 0.9206195019546656

orest Regression:
ared Error (MSE): 1558.0443567235197
olute Error (MAE): 3.468673217154869
d (R2): 0.9999000995115809
```

Hyper Parameter and Cross Validation

```
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import LabelEncoder

# Drop NaN values
df = df.dropna()

# Identify categorical columns
categorical_columns = []

# Apply Label Encoding for categorical features
label_encoder = LabelEncoder()
for col in categorical_columns:
    df[col] = label_encoder.fit_transform(df[col].astype(str))

# Splitting data
X = df.drop(columns=['price'])
y = df['price']


cat_columns = X.select_dtypes(include=['object']).columns

encoder_X = OneHotEncoder(drop='first', sparse_output=False)
X_encoded = encoder_X.fit_transform(X[cat_columns])

# Convert encoded features to DataFrame and concatenate with numerical features
X_encoded_df = pd.DataFrame(X_encoded, columns=encoder_X.get_feature_names_out(cat_columm
X = pd.concat([X.drop(columns=cat_columns), X_encoded_df], axis=1)

# Encode y (Sleep Disorder) using LabelEncoder (0: No, 1: Yes)
encoder_y = LabelEncoder()
y_encoded = encoder_y.fit_transform(y)

# Ensure no missing values in the target variable
y = y.fillna(y.mean())

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Hyperparameter tuning for Linear Regression
linear_params = {'fit_intercept': [True, False]}
linear_grid = GridSearchCV(LinearRegression(), param_grid=linear_params, cv=5)
linear_grid.fit(X_train, y_train)

# Hyperparameter tuning for Random Forest Regression
rf_params = {
    'n_estimators': [50, 100, 150],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
```

```
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt']
}
rf_grid = GridSearchCV(RandomForestRegressor(random_state=42), param_grid=rf_params, cv=!
rf_grid.fit(X_train, y_train)

print("Best Hyperparameters for Linear Regression:", linear_grid.best_params_)

print("Best Hyperparameters for Random Forest Regression:", rf_grid.best_params_)
```

```
Best Hyperparameters for Linear Regression: {'fit_intercept': True}
Best Hyperparameters for Random Forest Regression: {'max_depth': None, 'max_features
```

Feature selection using k best

```
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
import pandas as pd

# Assuming df is your dataframe

# Splitting data
X = df.drop(columns=['price'])
y = df['price']

# Identify categorical columns
categorical_columns = X.select_dtypes(include=['object']).columns
numerical_columns = X.select_dtypes(exclude=['object']).columns

# Create a column transformer to handle categorical and numerical features
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(sparse_output=False, handle_unknown='ignore'), categorical_c
        ('num', StandardScaler(), numerical_columns)
    ])

# Split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Apply the column transformer to the data
X_train_transformed = preprocessor.fit_transform(X_train)
X_test_transformed = preprocessor.transform(X_test)

# Get feature names after transformation
feature_names = preprocessor.get_feature_names_out()

# Feature selection setup
percentile = 0.8  # Select 80% of features
k_features = int(X_train_transformed.shape[1] * percentile)
```

```
# SelectKBest for Linear Regression and Random Forest Regression
selector = SelectKBest(f_regression, k=k_features)
X_train_selected = selector.fit_transform(X_train_transformed, y_train)
X_test_selected = selector.transform(X_test_transformed)

# Get selected feature indices and names
selected_features_indices = selector.get_support(indices=True)
selected_features = [feature_names[i] for i in selected_features_indices]

print("Selected features:", selected_features)
```

```
Selected features: ['cat__cut_Fair', 'cat__cut_Ideal', 'cat__cut_Premium', 'cat__colo
```

Final model

```
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
```