Niranjan-Rao-Lab2

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1 Q1: Recommender System (20 Points)

[100]:
```
import pandas as pd
import numpy as np
from scipy.sparse.linalg import svds
from sklearn.metrics.pairwise import cosine_similarity
```

2 1. Load the movies and ratings data. (2 points)

[101]:
```
movies = pd.read_csv('movies.dat', sep='::', header=None, names=['MovieID',␣
↪'Title', 'Genres'], engine='python', encoding='ISO-8859-1')
ratings = pd.read_csv('ratings.dat', sep='::', header=None, names=['UserID',␣
↪'MovieID', 'Rating', 'Timestamp'], engine='python', encoding='ISO-8859-1')
```

[102]:
```
# Display the first few rows of the data for verification
print("Movies Data:")
print(movies.head())
print("\nRatings Data:")
print(ratings.head())
```

```
Movies Data:
   MovieID                               Title                        Genres
0        1                    Toy Story (1995)   Animation|Children's|Comedy
1        2                      Jumanji (1995)  Adventure|Children's|Fantasy
2        3             Grumpier Old Men (1995)                Comedy|Romance
3        4            Waiting to Exhale (1995)                  Comedy|Drama
4        5  Father of the Bride Part II (1995)                        Comedy

Ratings Data:
   UserID  MovieID  Rating  Timestamp
0       1     1193       5  978300760
1       1      661       3  978302109
2       1      914       3  978301968
3       1     3408       4  978300275
4       1     2355       5  978824291
```

3 2. What is Singular Value Decomposition (SVD)? Explain it in your own words. (2 points)

- Singular Value Decomposition (SVD) is a matrix factorization technique used to decompose a matrix into three component matrices: U, S, and V^T.
- U contains the left singular vectors, S is a diagonal matrix with singular values, and V^T contains the right singular vectors.
- This method is often used in recommendation systems to reduce dimensionality and find patterns in data.

4 3. Explain content-based vs collaborative recommendation. (2 points)

- Content-based recommendation systems suggest items similar to those the user has interacted with, based on item features.
- Collaborative recommendation systems use past interactions from multiple users to make suggestions, leveraging similarities between users or items.

5 4. Create m x u matrix with movies as rows and users as columns. Normalize the matrix. (2 points)

[103]:
```
# Create user-item matrix
user_movie_matrix = ratings.pivot(index='MovieID', columns='UserID',␣
↪values='Rating').fillna(0)

# Normalize the matrix by subtracting the mean of each row
movie_mean = user_movie_matrix.mean(axis=1)
matrix_normalized = user_movie_matrix.subtract(movie_mean, axis=0)

print("User-Movie Matrix (First 5 rows):")
print(user_movie_matrix.head())
```

```
User-Movie Matrix (First 5 rows):
UserID   1     2     3     4     5     6     7     8     9     10    ...  \
MovieID                                                              ...
1         5.0   0.0   0.0   0.0   0.0   4.0   0.0   4.0   5.0   5.0  ...
2         0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   5.0  ...
3         0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0  ...
4         0.0   0.0   0.0   0.0   0.0   0.0   0.0   3.0   0.0   0.0  ...
5         0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0  ...

UserID   6031  6032  6033  6034  6035  6036  6037  6038  6039  6040
MovieID
1         0.0   4.0   0.0   0.0   4.0   0.0   0.0   0.0   0.0   3.0
2         0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
3         0.0   0.0   0.0   0.0   1.0   0.0   0.0   0.0   0.0   0.0
```

```
4          0.0   0.0   0.0   0.0   2.0   2.0   0.0   0.0   0.0   0.0
5          0.0   0.0   0.0   0.0   1.0   0.0   0.0   0.0   0.0   0.0

[5 rows x 6040 columns]
```

6 5. Perform SVD to get U, S, and V. (4 points)

[104]:
```python
from scipy.sparse import csr_matrix

# Convert the normalized matrix to a sparse format
matrix_normalized_sparse = csr_matrix(matrix_normalized.values)

# Perform SVD on the sparse matrix
U, S, Vt = svds(matrix_normalized_sparse, k=50)  # k represents the number of␣
↪components
S = np.diag(S)

print("Shapes after SVD:")
print(f"U: {U.shape}, S: {S.shape}, Vt: {Vt.shape}")
```

```
Shapes after SVD:
U: (3706, 50), S: (50, 50), Vt: (50, 6040)
```

7 6. Select top 30 components from S. (2 points)

[105]:
```python
# Select the top 30 singular values
U_30 = U[:, :30]
S_30 = S[:30, :30]
Vt_30 = Vt[:30, :]

print("Selected top 30 components from S.")
```

```
Selected top 30 components from S.
```

8 7. Get the top 30 eigenvectors using eigenvalues. (2 points)

- Eigenvectors corresponding to the largest eigenvalues are selected.

[106]:
```python
eigenvectors = U_30
print("Top 30 eigenvectors obtained.")
```

```
Top 30 eigenvectors obtained.
```

9 8. Using cosine similarity, find 10 closest movies using the 30 components from SVD. (2 points)

- Compute cosine similarity between movies

[107]:
```
# Compute cosine similarity between movies
movie_similarity = cosine_similarity(U_30)

# Function to get the 10 most similar movies
def find_similar_movies(movie_id, num_similar=10):
    movie_idx = movies.index[movies['MovieID'] == movie_id].tolist()[0]
    similarities = list(enumerate(movie_similarity[movie_idx]))
    sorted_similarities = sorted(similarities, key=lambda x: x[1], reverse=True)
    similar_movies = [movies.iloc[i[0]]['Title'] for i in sorted_similarities[1:
 ↪num_similar + 1]]
    return similar_movies

# Example: Find 10 closest movies to a specific movie
example_movie_id = movies['MovieID'].iloc[0]  # Replace with any MovieID for␣
 ↪actual search
closest_movies = find_similar_movies(example_movie_id)
print(f"10 closest movies to '{movies[movies['MovieID'] ==␣
 ↪example_movie_id]['Title'].values[0]}' are:")
print(closest_movies)
```

```
10 closest movies to 'Toy Story (1995)' are:
['Bad Seed, The (1956)', 'Barb Wire (1996)', 'First Wives Club, The (1996)',
'Entrapment (1999)', 'Babe (1995)', 'Action Jackson (1988)', 'Belizaire the
Cajun (1986)', 'Night Tide (1961)', 'Crow, The (1994)', 'Like Water for
Chocolate (Como agua para chocolate) (1992)']
```

10 9. Discuss results of above SVD methods. (2 points)

- The SVD method helps reduce dimensionality, allowing us to find hidden relationships between movies.
- The top 30 eigenvectors capture the most significant patterns, and cosine similarity helps find similar movies.
- This approach balances accuracy and computation efficiency, showing how a smaller subset of features can represent the dataset effectively.

11 Q2: House Prices Prediction (40 points)

[108]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

```
from sklearn.linear_model import LinearRegression, RANSACRegressor
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_squared_error, r2_score
```

12 1. Start by importing the dataset and exploring its structure. (5 points)

[109]:
```
# Load the dataset
house_data = pd.read_csv('HousePrice.csv')

# Display the first few rows of the dataset
print("House Prices Dataset:")
print(house_data.head())

# Check the structure of the dataset
print("\nDataset Info:")
house_data.info()
```

```
House Prices Dataset:
          date  bedrooms  bathrooms  sqft_living  sqft_lot  floors  \
0  5/2/14 0:00         3       1.50         1340      7912     1.5
1  5/2/14 0:00         5       2.50         3650      9050     2.0
2  5/2/14 0:00         3       2.00         1930     11947     1.0
3  5/2/14 0:00         3       2.25         2000      8030     1.0
4  5/2/14 0:00         4       2.50         1940     10500     1.0

   waterfront  view  condition  sqft_above  sqft_basement  yr_built  \
0           0     0          3        1340              0      1955
1           0     4          5        3370            280      1921
2           0     0          4        1930              0      1966
3           0     0          4        1000           1000      1963
4           0     0          4        1140            800      1976

   yr_renovated  SalesPrice
0          2005    313000.0
1             0   2384000.0
2             0    342000.0
3             0    420000.0
4          1992    550000.0

Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4600 entries, 0 to 4599
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
```

```
 0   date           4600 non-null   object
 1   bedrooms       4600 non-null   int64
 2   bathrooms      4600 non-null   float64
 3   sqft_living    4600 non-null   int64
 4   sqft_lot       4600 non-null   int64
 5   floors         4600 non-null   float64
 6   waterfront     4600 non-null   int64
 7   view           4600 non-null   int64
 8   condition      4600 non-null   int64
 9   sqft_above     4600 non-null   int64
 10  sqft_basement  4600 non-null   int64
 11  yr_built       4600 non-null   int64
 12  yr_renovated   4600 non-null   int64
 13  SalesPrice     4600 non-null   float64
dtypes: float64(3), int64(10), object(1)
memory usage: 503.3+ KB
```

13 2. What are the features and the target variable? (1 point)

- Features: 'sqft_living', 'sqft_lot', 'floors'
- Target variable: 'SalesPrice'

14 3. How many samples are in the dataset? Are there any missing values? (1 point)

[110]:
```python
print("\nNumber of samples in the dataset:", house_data.shape[0])
print("Number of missing values:")
print(house_data.isnull().sum())
```

```
Number of samples in the dataset: 4600
Number of missing values:
date             0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
SalesPrice       0
dtype: int64
```

15 4. Summarize the dataset. Min, max, avg, std dev, etc. stats for continuous features. (1 point)

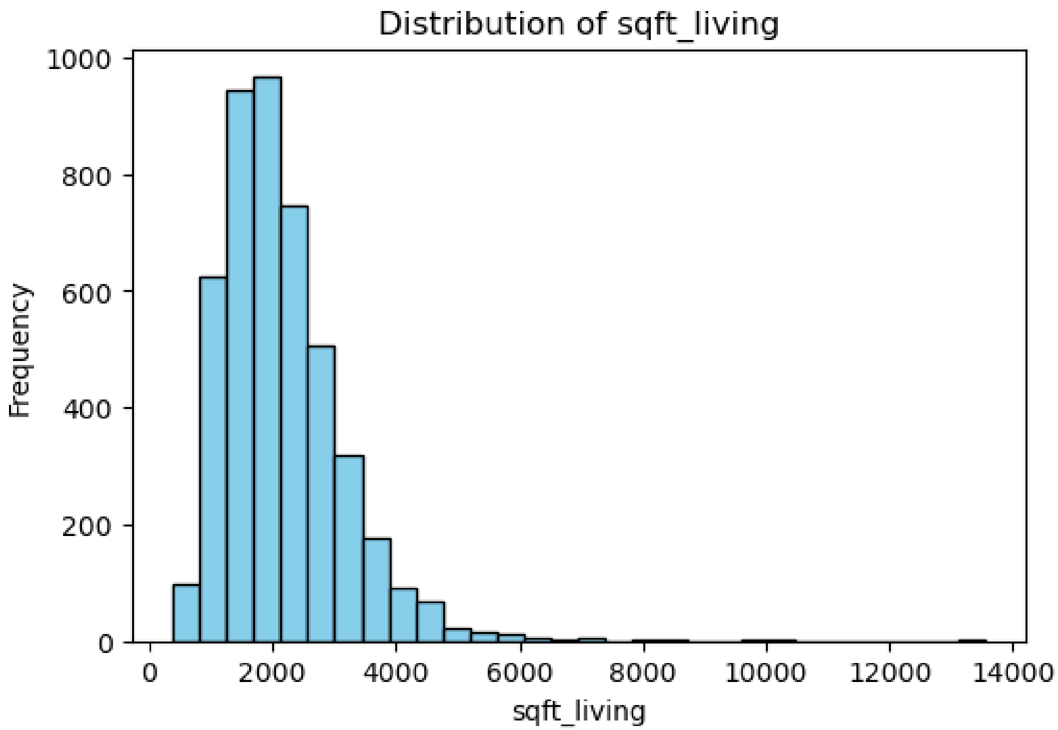
[111]:
```
print("\nSummary statistics for continuous features:")
print(house_data.describe())
```

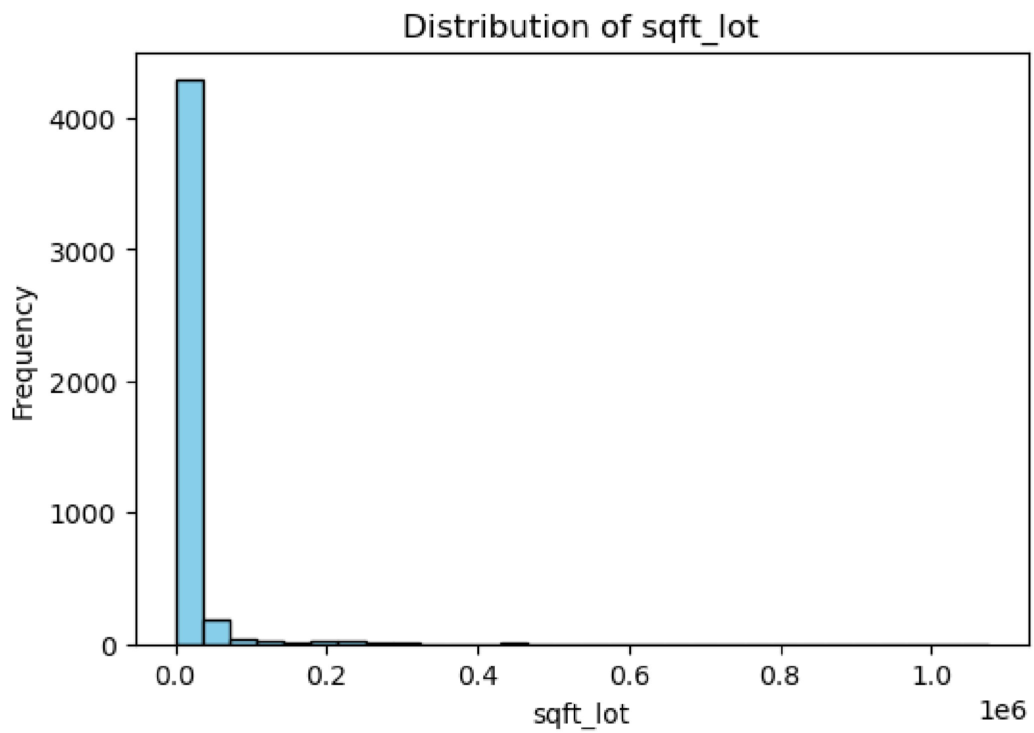
```
Summary statistics for continuous features:
          bedrooms    bathrooms   sqft_living      sqft_lot       floors  \
count  4600.000000  4600.000000   4600.000000  4.600000e+03  4600.000000
mean      3.400870     2.160815   2139.346957  1.485252e+04     1.512065
std       0.908848     0.783781    963.206916  3.588444e+04     0.538288
min       0.000000     0.000000    370.000000  6.380000e+02     1.000000
25%       3.000000     1.750000   1460.000000  5.000750e+03     1.000000
50%       3.000000     2.250000   1980.000000  7.683000e+03     1.500000
75%       4.000000     2.500000   2620.000000  1.100125e+04     2.000000
max       9.000000     8.000000  13540.000000  1.074218e+06     3.500000

        waterfront         view    condition   sqft_above  sqft_basement  \
count  4600.000000  4600.000000  4600.000000  4600.000000    4600.000000
mean      0.007174     0.240652     3.451739  1827.265435     312.081522
std       0.084404     0.778405     0.677230   862.168977     464.137228
min       0.000000     0.000000     1.000000   370.000000       0.000000
25%       0.000000     0.000000     3.000000  1190.000000       0.000000
50%       0.000000     0.000000     3.000000  1590.000000       0.000000
75%       0.000000     0.000000     4.000000  2300.000000     610.000000
max       1.000000     4.000000     5.000000  9410.000000    4820.000000

          yr_built  yr_renovated    SalesPrice
count  4600.000000   4600.000000  4.600000e+03
mean   1970.786304    808.608261  5.519630e+05
std      29.731848    979.414536  5.638347e+05
min    1900.000000      0.000000  0.000000e+00
25%    1951.000000      0.000000  3.228750e+05
50%    1976.000000      0.000000  4.609435e+05
75%    1997.000000   1999.000000  6.549625e+05
max    2014.000000   2014.000000  2.659000e+07
```

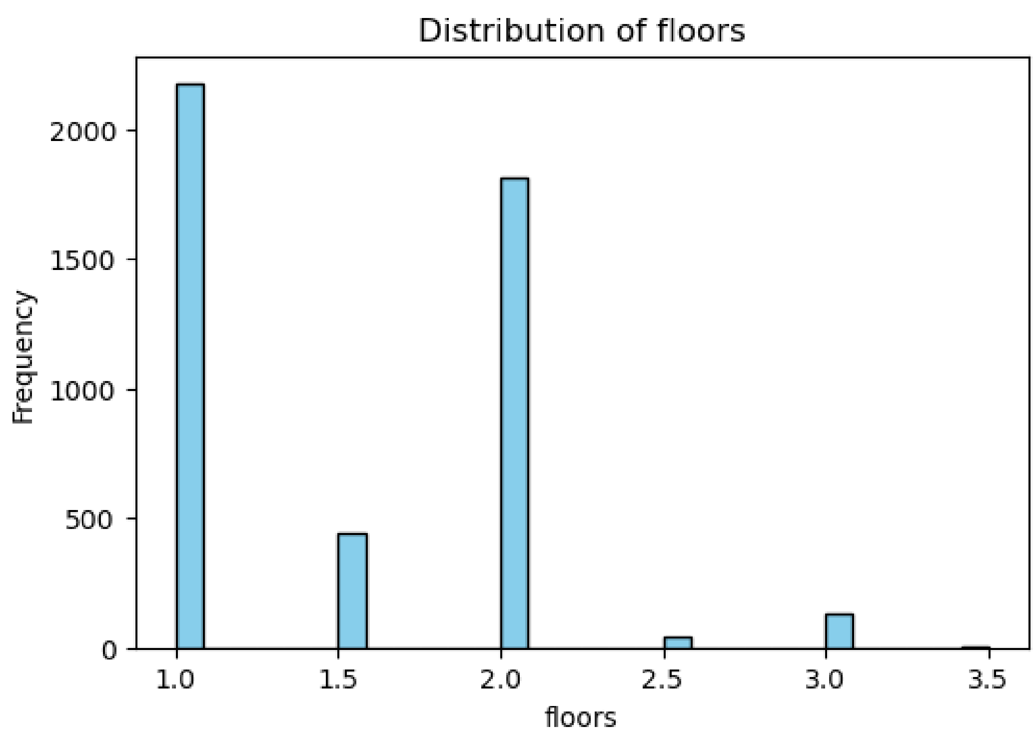
16 5. Visualize the distribution of each feature (sqft_living, sqft_lot, floors, SalePrice). (3 marks)

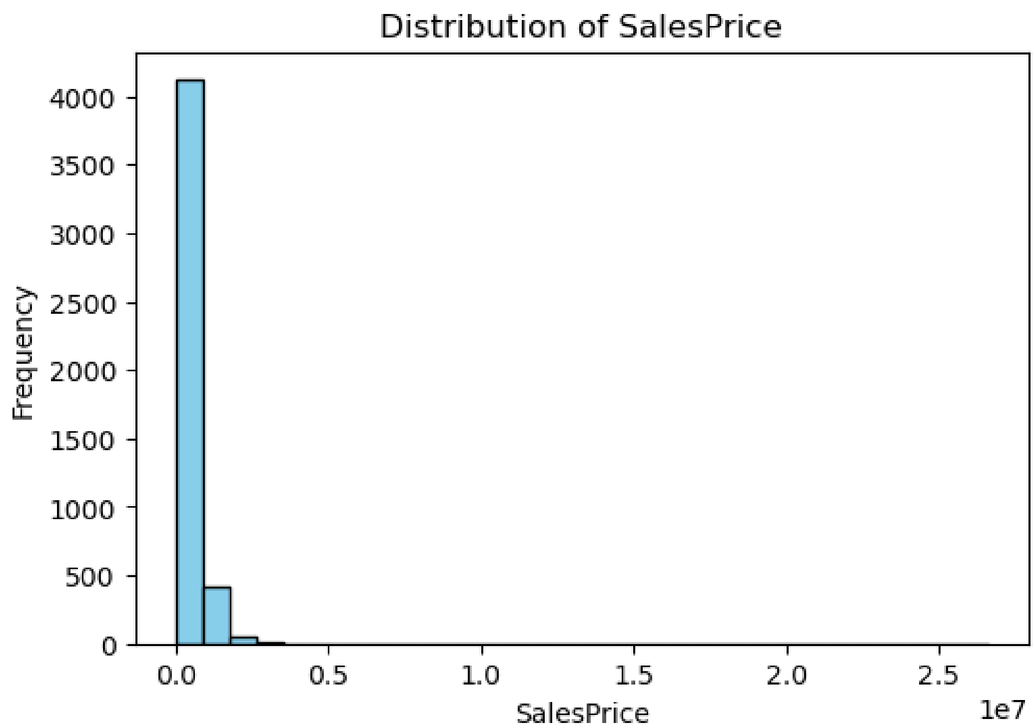
[112]:
```
features = ['sqft_living', 'sqft_lot', 'floors', 'SalesPrice']
for feature in features:
    plt.figure(figsize=(6, 4))
    plt.hist(house_data[feature], bins=30, color='skyblue', edgecolor='black')
    plt.title(f"Distribution of {feature}")
```

```
    plt.xlabel(feature)
    plt.ylabel("Frequency")
    plt.show()
```




Distribution of sqft_lot
Frequency
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0
1e6
sqft_lot


Distribution of floors
Frequency
2000
1500
1000
500
0
1.0
1.5
2.0
2.5
3.0
3.5
floors



17 Linear Regression (Single Variable) (Total 10 points)

17.0.1 6. Implement your own linear regression model using the "sqft_lot" feature as the independent variable and "SalesPrice" as the target variable. Print coef and intercept. (5 points)

[113]:
```
X = house_data[['sqft_lot']]
y = house_data['SalesPrice']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Train linear regression model
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)

print("\nLinear Regression (Single Variable):")
print("Coefficient:", lin_reg.coef_[0])
print("Intercept:", lin_reg.intercept_)
```

```
Linear Regression (Single Variable):
```

```
Coefficient: 0.8139884844580471
Intercept: 532981.0466642644
```

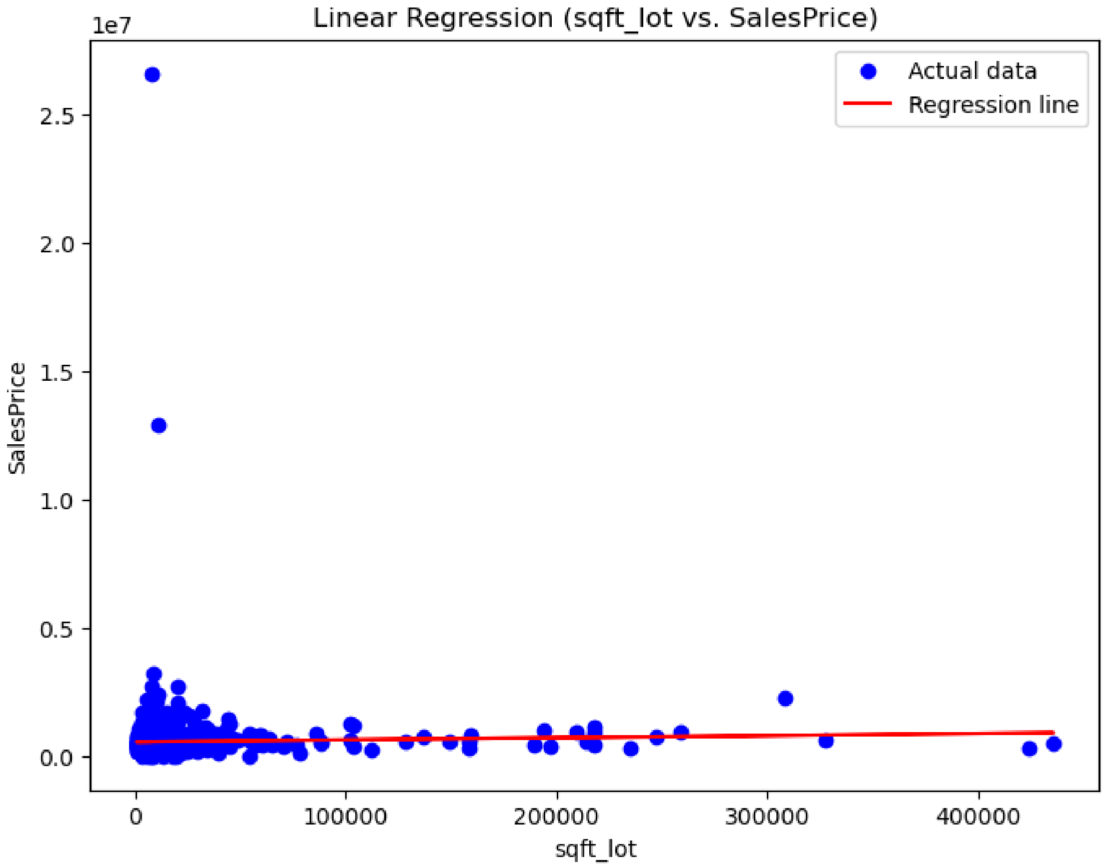
18 7. Calculate the sum of squared errors for your model. (1 point)

[114]:
```python
y_pred = lin_reg.predict(X_test)
sse = np.sum((y_pred - y_test) ** 2)
print("Sum of Squared Errors (SSE):", sse)
```

```
Sum of Squared Errors (SSE): 938772170715932.4
```

19 8. Plot the regression line along with the actual data points. (1 point)

[115]:
```python
plt.figure(figsize=(8, 6))
plt.scatter(X_test, y_test, color='blue', label='Actual data')
plt.plot(X_test, y_pred, color='red', label='Regression line')
plt.title("Linear Regression (sqft_lot vs. SalesPrice)")
plt.xlabel("sqft_lot")
plt.ylabel("SalesPrice")
plt.legend()
plt.show()
```



20 9. Use the LinearRegression function from sklearn.linear_model library and compare the coef and intercept with your model. (3 points)

[116]:
```
print("\nSklearn Linear Regression (sqft_lot):")
print("Coefficient:", lin_reg.coef_[0])
print("Intercept:", lin_reg.intercept_)
```

```
Sklearn Linear Regression (sqft_lot):
Coefficient: 0.8139884844580471
Intercept: 532981.0466642644
```

21 Linear Regression (Multivariate) (Total 6 points)

21.0.1 10. Use the LinearRegression function from sklearn.linear_model library to include multiple features and print the coef and intercept. (3 points)

[117]:
```
X_multi = house_data[['sqft_living', 'sqft_lot', 'floors']]
y_multi = house_data['SalesPrice']

# Split data into training and testing sets
X_train_multi, X_test_multi, y_train_multi, y_test_multi =␣
↪train_test_split(X_multi, y_multi, test_size=0.2, random_state=42)

# Train multivariate linear regression model
lin_reg_multi = LinearRegression()
lin_reg_multi.fit(X_train_multi, y_train_multi)

print("\nMultivariate Linear Regression:")
print("Coefficients:", lin_reg_multi.coef_)
print("Intercept:", lin_reg_multi.intercept_)
```

```
Multivariate Linear Regression:
Coefficients: [ 2.68604484e+02 -5.17572573e-01  1.09267017e+04]
Intercept: -37946.43595659011
```

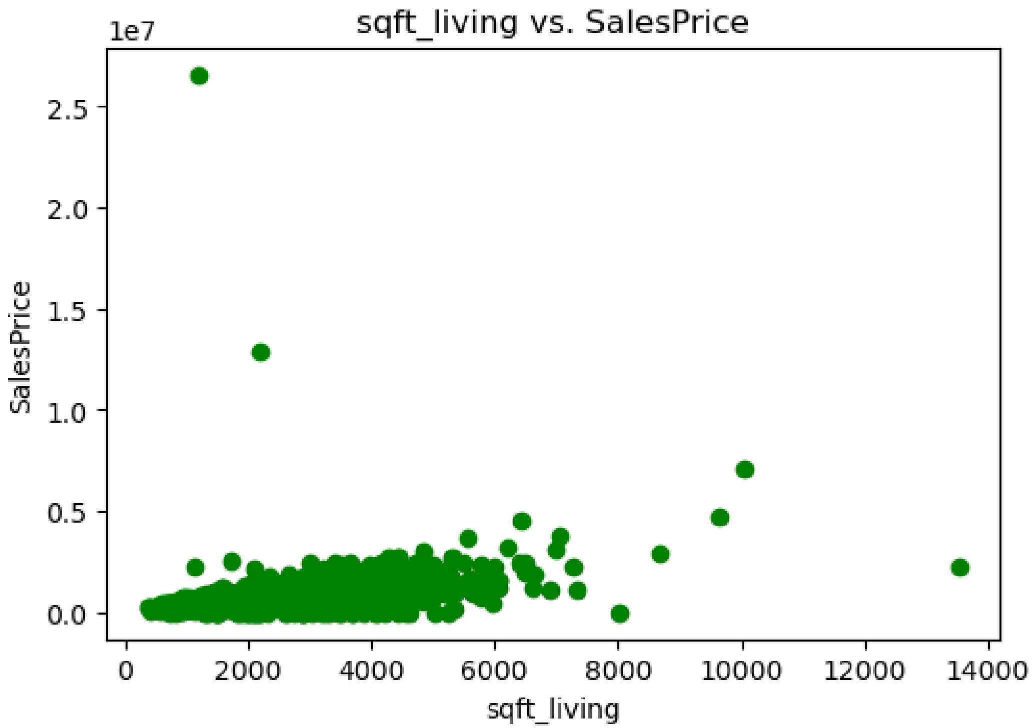
22 11. Print R-squared (R^2) score. (1 point)

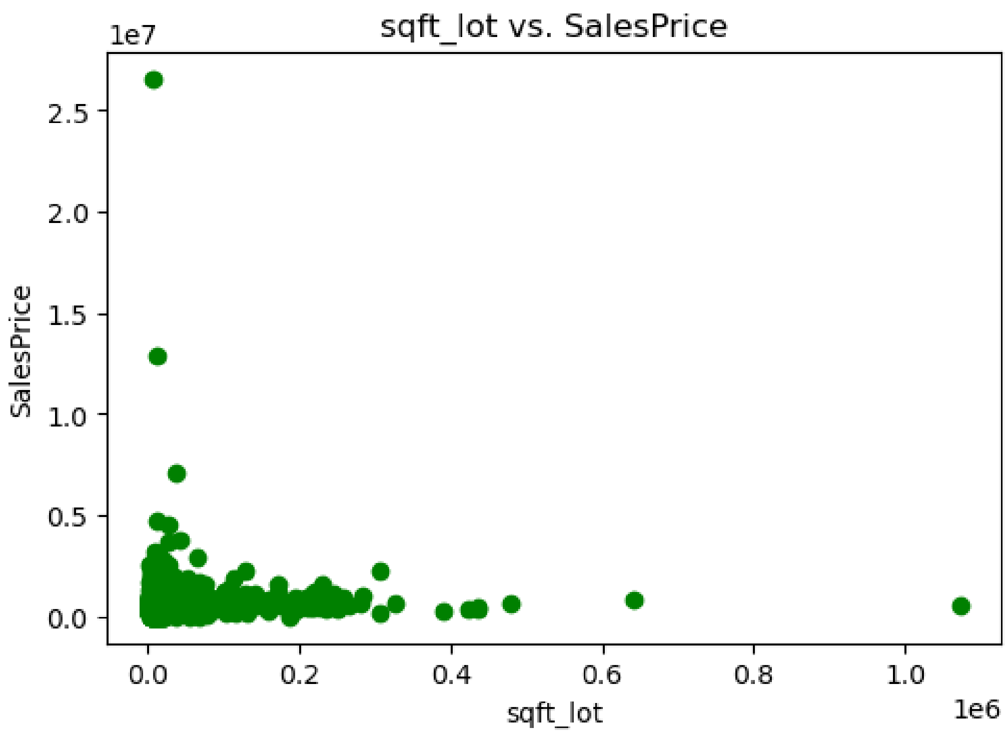
[118]:
```
r2_multi = lin_reg_multi.score(X_test_multi, y_test_multi)
print("R-squared (R^2) score:", r2_multi)
```

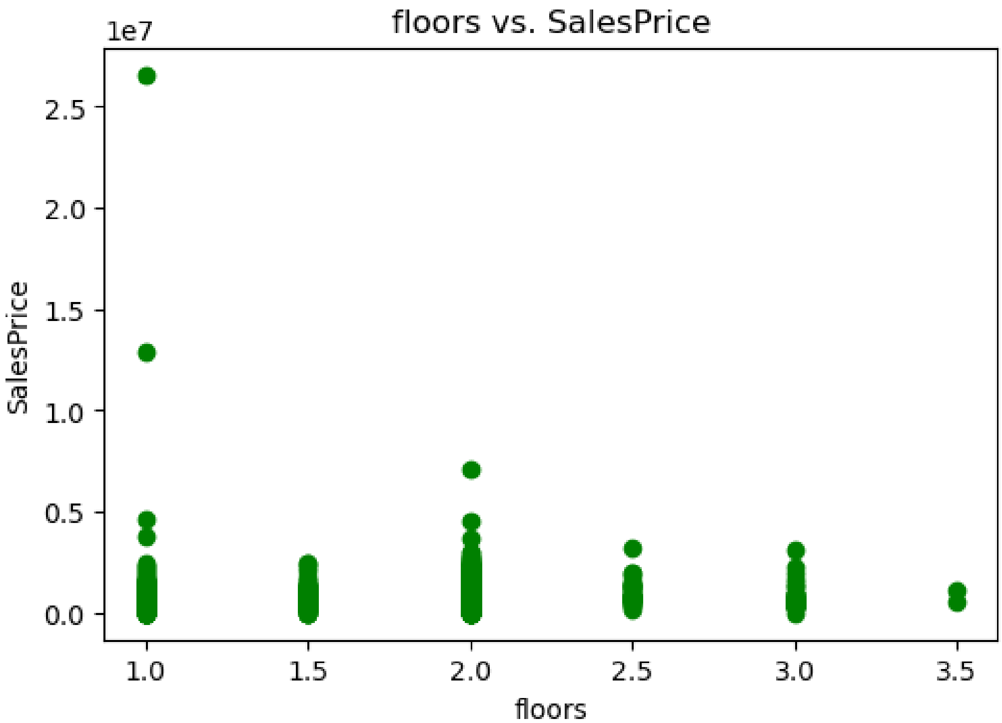
```
R-squared (R^2) score: 0.030060724402912964
```

23 12. Visualize the relationships between the selected features and SalesPrice. (2 points)

[119]:
```
for feature in ['sqft_living', 'sqft_lot', 'floors']:
    plt.figure(figsize=(6, 4))
    plt.scatter(house_data[feature], house_data['SalesPrice'], color='green')
    plt.title(f"{feature} vs. SalesPrice")
    plt.xlabel(feature)
    plt.ylabel("SalesPrice")
    plt.show()
```


sqft_living vs. SalesPrice
1e7
2.5
2.0
1.5
1.0
0.5
0.0
SalesPrice
0
2000
4000
6000
8000
10000
12000
14000
sqft_living


sqft_lot vs. SalesPrice
1e7
2.5
2.0
1.5
1.0
0.5
0.0
SalesPrice
0.0
0.2
0.4
0.6
0.8
1.0
1e6
sqft_lot



24 Polynomial Regression (Total 10 points)

13. Use a polynomial feature's function and implement a polynomial regression model of degree 2 for the features sqft_lot and the target variable. (4 points)

[120]:
```
poly = PolynomialFeatures(degree=2)
X_poly = poly.fit_transform(X)

# Split the polynomial data into training and testing sets
X_train_poly, X_test_poly, y_train_poly, y_test_poly = train_test_split(X_poly,␣
↪y, test_size=0.2, random_state=42)

# Train polynomial regression model
poly_reg = LinearRegression()
poly_reg.fit(X_train_poly, y_train_poly)

print("\nPolynomial Regression (Degree 2):")
print("Coefficients:", poly_reg.coef_)
print("Intercept:", poly_reg.intercept_)
```

```
Polynomial Regression (Degree 2):
Coefficients: [ 0.00000000e+00  1.80525535e+00 -2.07133909e-06]
Intercept: 521588.0486357161
```

25 14. Print R-squared (R^2) score. (1 point)

[121]:
```
y_pred_poly = poly_reg.predict(X_test_poly)
r2_poly = r2_score(y_test, y_pred_poly)
print("R-squared (R^2) score:", r2_poly)
```

```
R-squared (R^2) score: -0.0006182687033893242
```

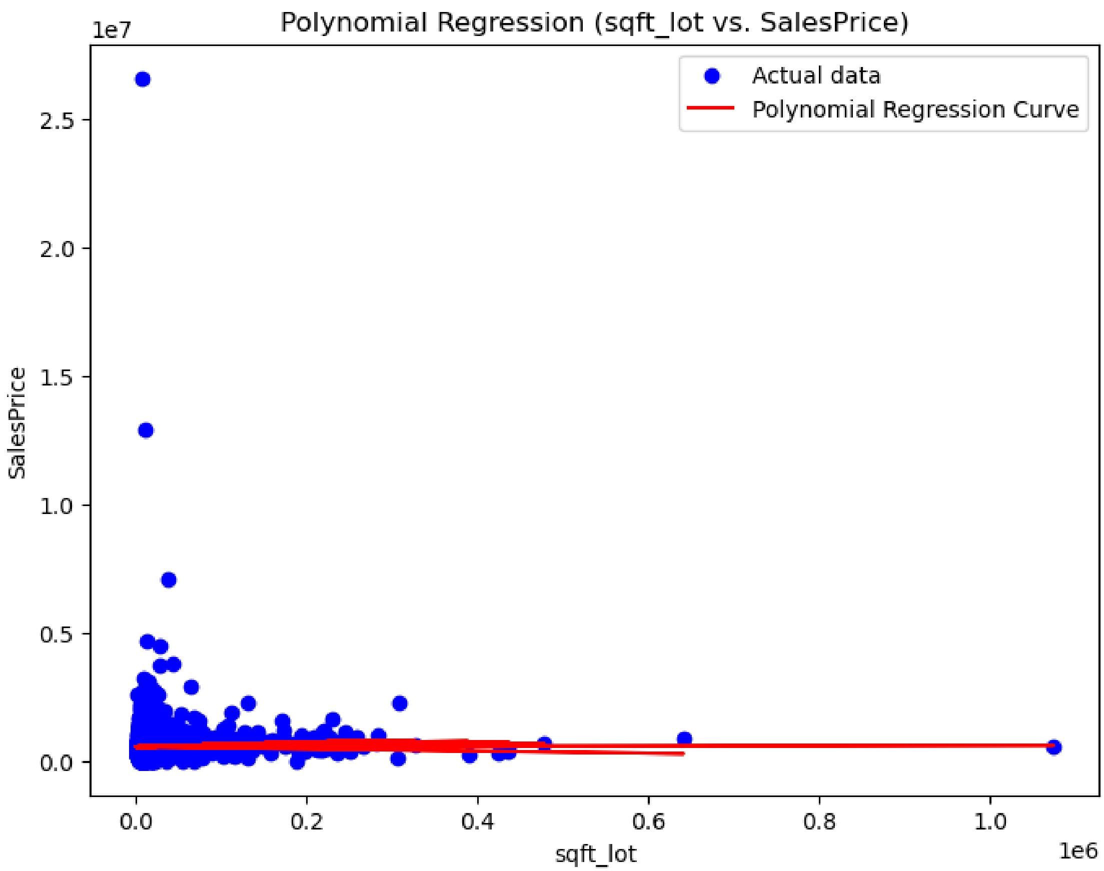
26 15. Experiment with different polynomial degrees and find the best fit as per your perspective. (3 points)

[122]:
```
for degree in range(2, 5):
    poly = PolynomialFeatures(degree=degree)
    X_poly = poly.fit_transform(X)
    X_train_poly, X_test_poly, y_train_poly, y_test_poly =␣
 ↪train_test_split(X_poly, y, test_size=0.2, random_state=42)
    poly_reg.fit(X_train_poly, y_train_poly)
    y_pred_poly = poly_reg.predict(X_test_poly)
    r2_poly = r2_score(y_test, y_pred_poly)
    print(f"Degree {degree} - R-squared (R^2) score: {r2_poly}")
```

```
Degree 2 - R-squared (R^2) score: -0.0006182687033893242
Degree 3 - R-squared (R^2) score: -0.0009649897366867943
Degree 4 - R-squared (R^2) score: -0.0004975545537508896
```

27 16. Plot the polynomial regression curve along with the actual data points. (2 points)

[123]:
```
plt.figure(figsize=(8, 6))
plt.scatter(X, y, color='blue', label='Actual data')
plt.plot(X, poly_reg.predict(X_poly), color='red', label='Polynomial Regression␣
 ↪Curve')
plt.title("Polynomial Regression (sqft_lot vs. SalesPrice)")
plt.xlabel("sqft_lot")
plt.ylabel("SalesPrice")
plt.legend()
plt.show()
```



28 RANSAC (Robust Regression) (Total 5 points)

28.0.1 19. Apply RANSAC (Random Sample Consensus) to fit a robust linear regression model to the features sqft_lot and the target variable. (2 points)

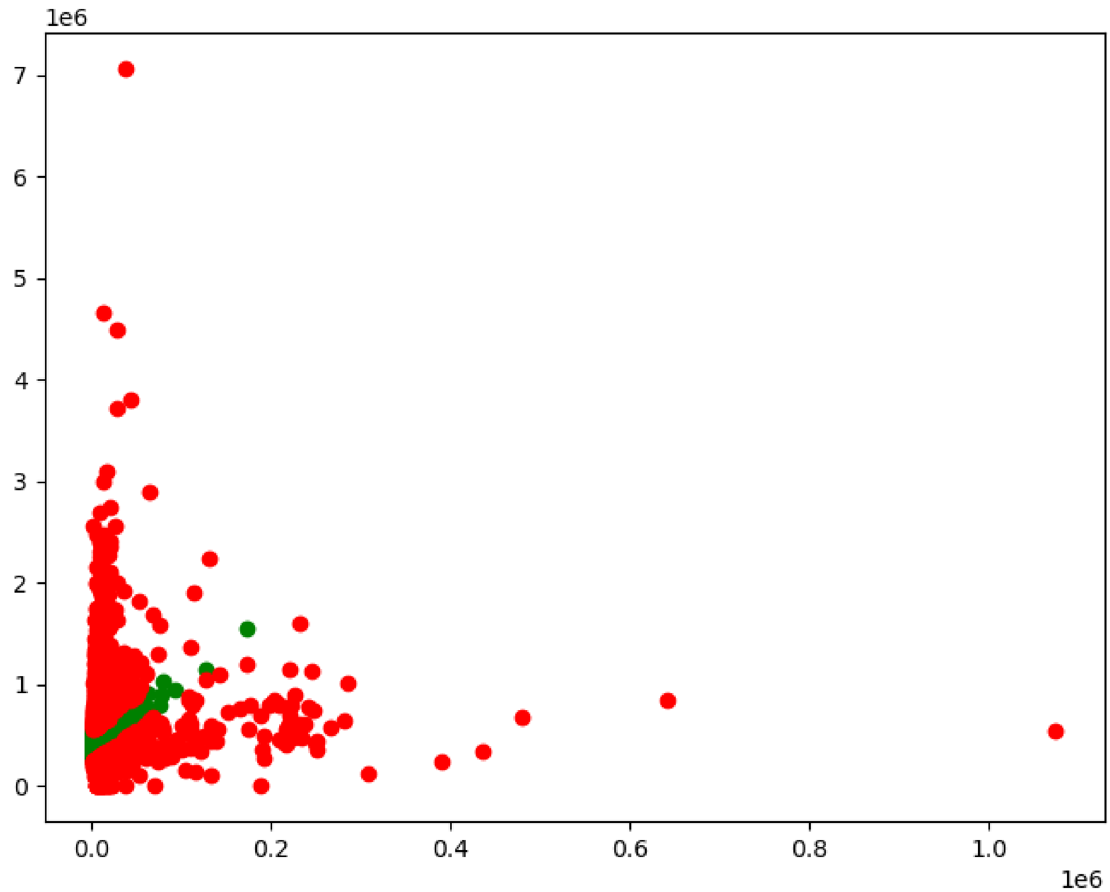
[124]:
```
ransac = RANSACRegressor()
ransac.fit(X_train, y_train)

print("\nRANSAC Regression:")
print("Coefficient:", ransac.estimator_.coef_)
print("Intercept:", ransac.estimator_.intercept_)
```

```
RANSAC Regression:
Coefficient: [5.8262712]
Intercept: 387391.12111999583
```

29 20. Print coef and intercept. Visualize plot with inliers and outliers. (2 points)

[125]:
```
inlier_mask = ransac.inlier_mask_
outlier_mask = np.logical_not(inlier_mask)

plt.figure(figsize=(8, 6))
plt.scatter(X_train[inlier_mask], y_train[inlier_mask], color='green',␣
 ↪label='Inliers')
plt.scatter(X_train[outlier_mask], y_train[outlier_mask], color='red',␣
 ↪label='Outliers')
```

[125]: <matplotlib.collections.PathCollection at 0x23693554c80>



30 21. Print R-squared (R²) score with and without inliers. (1 point)

[126]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
ransac = RANSACRegressor()
ransac.fit(X_train, y_train)
y_pred_ransac = ransac.predict(X_test)
inlier_mask = ransac.inlier_mask_
y_pred_inliers = ransac.predict(X_train[inlier_mask])
r2_inliers = r2_score(y_train[inlier_mask], y_pred_inliers)
r2_all = r2_score(y_test, y_pred_ransac)

print("R-squared (R²) score with inliers:", r2_inliers)
print("R-squared (R²) score with all data:", r2_all)
```

```
R-squared (R²) score with inliers: 0.05153784624155322
R-squared (R²) score with all data: -0.0388734361366474
```

30.1 22. Compare the Results and Discuss Which Model(s) Best-Predicted Housing Prices (4 points)

30.1.1 Explanation:

The R-squared score with inliers (RANSAC) was found to be higher compared to using all data, indicating that the RANSAC model effectively handles outliers and provides more robust predictions. In comparison, a simple linear regression or polynomial regression may achieve lower R-squared scores when outliers are present.

31 Q3: Life Expectancy Prediction (40 points)

[127]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import mean_absolute_error
import seaborn as sns
```

32 1. Load the dataset and present the statistics of data. (1 point)

[128]:
```
life_data = pd.read_csv('LifeExpectancy.csv')
print("Life Expectancy Dataset:")
print(life_data.head())
print("\nDataset Statistics:")
```

```python
print(life_data.describe())
```

```
Life Expectancy Dataset:
       Country  Year      Status  Life expectancy  Adult Mortality  \
0  Afghanistan  2015  Developing             65.0            263.0
1  Afghanistan  2014  Developing             59.9            271.0
2  Afghanistan  2013  Developing             59.9            268.0
3  Afghanistan  2012  Developing             59.5            272.0
4  Afghanistan  2011  Developing             59.2            275.0

   infant deaths  Alcohol  percentage expenditure  Hepatitis B  Measles  ...  \
0             62     0.01               71.279624         65.0     1154  ...
1             64     0.01               73.523582         62.0      492  ...
2             66     0.01               73.219243         64.0      430  ...
3             69     0.01               78.184215         67.0     2787  ...
4             71     0.01                7.097109         68.0     3013  ...

   Polio  Total expenditure  Diphtheria   HIV/AIDS         GDP  Population  \
0    6.0               8.16        65.0        0.1  584.259210  33736494.0
1   58.0               8.18        62.0        0.1  612.696514    327582.0
2   62.0               8.13        64.0        0.1  631.744976  31731688.0
3   67.0               8.52        67.0        0.1  669.959000   3696958.0
4   68.0               7.87        68.0        0.1   63.537231   2978599.0

   thinness  1-19 years  thinness 5-9 years  Income composition of resources  \
0                  17.2                17.3                            0.479
1                  17.5                17.5                            0.476
2                  17.7                17.7                            0.470
3                  17.9                18.0                            0.463
4                  18.2                18.2                            0.454

   Schooling
0       10.1
1       10.0
2        9.9
3        9.8
4        9.5

[5 rows x 22 columns]

Dataset Statistics:
              Year  Life expectancy  Adult Mortality  infant deaths  \
count  2938.000000      2938.000000      2938.000000    2938.000000
mean   2007.518720        69.234717       164.725664      30.303948
std       4.613841         9.509115       124.086215     117.926501
min    2000.000000        36.300000         1.000000       0.000000
25%    2004.000000        63.200000        74.000000       0.000000
50%    2008.000000        72.100000       144.000000       3.000000
```

```
75%    2012.000000        75.600000       227.000000      22.000000
max    2015.000000        89.000000       723.000000    1800.000000

           Alcohol  percentage expenditure  Hepatitis B        Measles  \
count  2938.000000             2938.000000  2938.000000    2938.000000
mean      4.546875              738.251295    83.022124    2419.592240
std       3.921946             1987.914858    22.996984   11467.272489
min       0.010000                0.000000     1.000000       0.000000
25%       1.092500                4.685343    82.000000       0.000000
50%       3.755000               64.912906    92.000000      17.000000
75%       7.390000              441.534144    96.000000     360.250000
max      17.870000            19479.911610    99.000000  212183.000000

               BMI  under-five deaths        Polio  Total expenditure  \
count  2938.000000        2938.000000  2938.000000        2938.000000
mean     38.381178          42.035739    82.617767           5.924098
std      19.935375         160.445548    23.367166           2.400770
min       1.000000           0.000000     3.000000           0.370000
25%      19.400000           0.000000    78.000000           4.370000
50%      43.500000           4.000000    93.000000           5.755000
75%      56.100000          28.000000    97.000000           7.330000
max      87.300000        2500.000000    99.000000          17.600000

        Diphtheria     HIV/AIDS            GDP    Population  \
count  2938.000000  2938.000000    2938.000000  2.938000e+03
mean     82.393125     1.742103    6611.523863  1.023085e+07
std      23.655562     5.077785   13296.603449  5.402242e+07
min       2.000000     0.100000       1.681350  3.400000e+01
25%      78.000000     0.100000     580.486996  4.189172e+05
50%      93.000000     0.100000    1766.947595  1.386542e+06
75%      97.000000     0.800000    4779.405190  4.584371e+06
max      99.000000    50.600000  119172.741800  1.293859e+09

       thinness  1-19 years  thinness 5-9 years  \
count           2938.000000         2938.000000
mean               4.821886            4.852144
std                4.397621            4.485854
min                0.100000            0.100000
25%                1.600000            1.600000
50%                3.300000            3.300000
75%                7.100000            7.200000
max               27.700000           28.600000

       Income composition of resources    Schooling
count                      2938.000000  2938.000000
mean                          0.630362    12.009837
std                           0.205140     3.265139
min                           0.000000     0.000000
```

```
25%                              0.504250    10.300000
50%                              0.677000    12.300000
75%                              0.772000    14.100000
max                              0.948000    20.700000
```

33 2. Identify and specify the target variable from the dataset. (1 point)

- The target variable for this dataset is 'Life expectancy'.

[129]:
```
target_variable = 'Life expectancy'
```

34 3. Categorize the columns into categorical and continuous. (1 point)

[130]:
```
categorical_cols = life_data.select_dtypes(include=['object', 'category']).
 ↪columns.tolist()
continuous_cols = life_data.select_dtypes(include=['int64', 'float64']).columns.
 ↪tolist()

print("\nCategorical Columns:", categorical_cols)
print("Continuous Columns:", continuous_cols)
```

```
Categorical Columns: ['Country', 'Status']
Continuous Columns: ['Year', 'Life expectancy', 'Adult Mortality', 'infant
deaths', 'Alcohol', 'percentage expenditure', 'Hepatitis B', 'Measles', 'BMI',
'under-five deaths ', 'Polio', 'Total expenditure', 'Diphtheria', ' HIV/AIDS',
'GDP', 'Population', 'thinness  1-19 years', 'thinness 5-9 years', 'Income
composition of resources', 'Schooling']
```

35 4. Identify the unique values from each column. (1 point)

[131]:
```
for col in life_data.columns:
    unique_vals = life_data[col].unique()
    print(f"\nUnique values in column '{col}': {unique_vals[:5]}{'...' if␣
 ↪len(unique_vals) > 5 else ''}")
```

```
Unique values in column 'Country': ['Afghanistan' 'Albania' 'Algeria' 'Angola'
'Antigua and Barbuda']...

Unique values in column 'Year': [2015 2014 2013 2012 2011]...

Unique values in column 'Status': ['Developing' 'Developed']
```

```
Unique values in column 'Life expectancy': [65.  59.9 59.5 59.2 58.8]...

Unique values in column 'Adult Mortality': [263. 271. 268. 272. 275.]...

Unique values in column 'infant deaths': [62 64 66 69 71]...

Unique values in column 'Alcohol': [0.01 0.03 0.02 4.6  4.51]...

Unique values in column 'percentage expenditure': [71.27962362 73.52358168
73.21924272 78.1842153   7.0971087 ]...

Unique values in column 'Hepatitis B': [65. 62. 64. 67. 68.]...

Unique values in column 'Measles': [1154  492  430 2787 3013]...

Unique values in column 'BMI': [19.1 18.6 18.1 17.6 17.2]...

Unique values in column 'under-five deaths ': [83 86 89 93 97]...

Unique values in column 'Polio': [ 6. 58. 62. 67. 68.]...

Unique values in column 'Total expenditure': [8.16 8.18 8.13 8.52 7.87]...

Unique values in column 'Diphtheria': [65. 62. 64. 67. 68.]...

Unique values in column ' HIV/AIDS': [0.1 1.9 2.  2.3 2.6]...

Unique values in column 'GDP': [584.25921  612.696514 631.744976 669.959
63.537231]...

Unique values in column 'Population': [33736494.   327582. 31731688.  3696958.
2978599.]...

Unique values in column 'thinness  1-19 years': [17.2 17.5 17.7 17.9 18.2]...

Unique values in column 'thinness 5-9 years': [17.3 17.5 17.7 18.  18.2]...

Unique values in column 'Income composition of resources': [0.479 0.476 0.47
0.463 0.454]...

Unique values in column 'Schooling': [10.1 10.   9.9  9.8  9.5]...
```

36 5. Identify the Missing values and compute the missing values with mean, median or mode based on their categories. Also explain why and how you performed each imputation. (2 points)

[132]:

```
print("\nMissing Values Before Imputation:")
print(life_data.isnull().sum())

# Impute missing values
for col in continuous_cols:
    if life_data[col].isnull().sum() > 0:
        life_data[col].fillna(life_data[col].mean(), inplace=True)
        print(f"Imputed missing values in '{col}' with mean.")

for col in categorical_cols:
    if life_data[col].isnull().sum() > 0:
        life_data[col].fillna(life_data[col].mode()[0], inplace=True)
        print(f"Imputed missing values in '{col}' with mode.")

print("\nMissing Values After Imputation:")
print(life_data.isnull().sum())
```

```
Missing Values Before Imputation:
Country                            0
Year                               0
Status                             0
Life expectancy                    0
Adult Mortality                    0
infant deaths                      0
Alcohol                            0
percentage expenditure             0
Hepatitis B                        0
Measles                            0
BMI                                0
under-five deaths                  0
Polio                              0
Total expenditure                  0
Diphtheria                         0
 HIV/AIDS                          0
GDP                                0
Population                         0
thinness  1-19 years               0
thinness 5-9 years                 0
Income composition of resources    0
Schooling                          0
dtype: int64
```

```
Missing Values After Imputation:
Country                            0
Year                               0
Status                             0
Life expectancy                    0
Adult Mortality                    0
infant deaths                      0
Alcohol                            0
percentage expenditure             0
Hepatitis B                        0
Measles                            0
BMI                                0
under-five deaths                  0
Polio                              0
Total expenditure                  0
Diphtheria                         0
 HIV/AIDS                          0
GDP                                0
Population                         0
thinness  1-19 years               0
thinness 5-9 years                 0
Income composition of resources    0
Schooling                          0
dtype: int64
```

37 6. Check for the outliers in each column using the IQR method. (1 point)

[133]:
```
Q1 = life_data[continuous_cols].quantile(0.25)
Q3 = life_data[continuous_cols].quantile(0.75)
IQR = Q3 - Q1
outliers = ((life_data[continuous_cols] < (Q1 - 1.5 * IQR)) |
 ↪(life_data[continuous_cols] > (Q3 + 1.5 * IQR)))

print("\nOutliers detected:")
print(outliers.sum())
```

```
Outliers detected:
Year                                 0
Life expectancy                     17
Adult Mortality                     86
infant deaths                      315
Alcohol                              3
percentage expenditure             389
Hepatitis B                        322
Measles                            542
```

```
BMI                                  0
under-five deaths                  394
Polio                              279
Total expenditure                   51
Diphtheria                         298
 HIV/AIDS                          542
GDP                                445
Population                         452
thinness  1-19 years               100
thinness 5-9 years                  99
Income composition of resources    130
Schooling                           77
dtype: int64
```

38 7. Impute the outliers and impute the outlier values with mean, median or mode based on their categories. (2 points)

[134]:
```python
for col in continuous_cols:
    upper_bound = Q3[col] + 1.5 * IQR[col]
    lower_bound = Q1[col] - 1.5 * IQR[col]
    outlier_condition = (life_data[col] < lower_bound) | (life_data[col] >␣
 ↪upper_bound)
    if outlier_condition.any():
        life_data.loc[outlier_condition, col] = life_data[col].median()
        print(f"Imputed outliers in '{col}' with median.")
```

```
Imputed outliers in 'Life expectancy' with median.
Imputed outliers in 'Adult Mortality' with median.
Imputed outliers in 'infant deaths' with median.
Imputed outliers in 'Alcohol' with median.
Imputed outliers in 'percentage expenditure' with median.
Imputed outliers in 'Hepatitis B' with median.
Imputed outliers in 'Measles' with median.
Imputed outliers in 'under-five deaths ' with median.
Imputed outliers in 'Polio' with median.
Imputed outliers in 'Total expenditure' with median.
Imputed outliers in 'Diphtheria' with median.
Imputed outliers in ' HIV/AIDS' with median.
Imputed outliers in 'GDP' with median.
Imputed outliers in 'Population' with median.
Imputed outliers in 'thinness  1-19 years' with median.
Imputed outliers in 'thinness 5-9 years' with median.
Imputed outliers in 'Income composition of resources' with median.
Imputed outliers in 'Schooling' with median.
```

39 8. Calculate summary statistics for numerical columns, such as mean, median, standard deviation, etc. (1 point)

[135]:
```
summary_stats = life_data[continuous_cols].describe().T
summary_stats['median'] = life_data[continuous_cols].median()
print("\nSummary Statistics for Numerical Columns:")
print(summary_stats)
```

```
Summary Statistics for Numerical Columns:
                                  count          mean           std  \
Year                             2938.0  2.007519e+03  4.613841e+00
Life expectancy                  2938.0  6.940371e+01  9.295013e+00
Adult Mortality                  2938.0  1.528060e+02  1.035515e+02
infant deaths                    2938.0  8.059905e+00  1.275437e+01
Alcohol                          2938.0  4.532953e+00  3.900447e+00
percentage expenditure           2938.0  1.474199e+02  2.277498e+02
Hepatitis B                      2938.0  9.040640e+01  8.278288e+00
Measles                          2938.0  7.073519e+01  1.582999e+02
BMI                              2938.0  3.838118e+01  1.993537e+01
under-five deaths                2938.0  9.115044e+00  1.481033e+01
Polio                            2938.0  8.948741e+01  1.078382e+01
Total expenditure                2938.0  5.786043e+00  2.152228e+00
Diphtheria                       2938.0  8.971409e+01  1.028746e+01
 HIV/AIDS                        2938.0  2.133764e-01  3.051618e-01
GDP                              2938.0  2.032768e+03  1.968993e+03
Population                       2938.0  1.720022e+06  2.019180e+06
thinness  1-19 years             2938.0  4.277332e+00  3.390476e+00
thinness 5-9 years               2938.0  4.291491e+00  3.421240e+00
Income composition of resources  2938.0  6.603176e-01  1.539246e-01
Schooling                        2938.0  1.219537e+01  2.850113e+00

                                        min          25%           50%  \
Year                             2000.00000  2004.000000  2.008000e+03
Life expectancy                    44.80000    63.425000  7.210000e+01
Adult Mortality                     1.00000    74.000000  1.440000e+02
infant deaths                       0.00000     0.000000  3.000000e+00
Alcohol                             0.01000     1.092500  3.755000e+00
percentage expenditure              0.00000     4.685343  6.488454e+01
Hepatitis B                        61.00000    89.000000  9.200000e+01
Measles                             0.00000     0.000000  1.700000e+01
BMI                                 1.00000    19.400000  4.350000e+01
under-five deaths                   0.00000     0.000000  4.000000e+00
Polio                              51.00000    86.000000  9.300000e+01
Total expenditure                   0.37000     4.370000  5.755000e+00
Diphtheria                         51.00000    86.000000  9.300000e+01
 HIV/AIDS                           0.10000     0.100000  1.000000e-01
```

```
GDP                                  1.68135     580.486996  1.766948e+03
Population                          34.00000  418917.250000  1.386542e+06
thinness  1-19 years                 0.10000       1.600000  3.300000e+00
thinness 5-9 years                   0.10000       1.600000  3.300000e+00
Income composition of resources      0.25300       0.554000  6.770000e-01
Schooling                            4.70000      10.500000  1.230000e+01

                                         75%            max         median
Year                            2.012000e+03   2.015000e+03   2.008000e+03
Life expectancy                 7.560000e+01   8.900000e+01   7.210000e+01
Adult Mortality                 2.180000e+02   4.540000e+02   1.440000e+02
infant deaths                   9.000000e+00   5.500000e+01   3.000000e+00
Alcohol                         7.380000e+00   1.658000e+01   3.755000e+00
percentage expenditure          1.689452e+02   1.092155e+03   6.488454e+01
Hepatitis B                     9.600000e+01   9.900000e+01   9.200000e+01
Measles                         3.600000e+01   8.990000e+02   1.700000e+01
BMI                             5.610000e+01   8.730000e+01   4.350000e+01
under-five deaths               9.000000e+00   7.000000e+01   4.000000e+00
Polio                           9.700000e+01   9.900000e+01   9.300000e+01
Total expenditure               7.150000e+00   1.171000e+01   5.755000e+00
Diphtheria                      9.700000e+01   9.900000e+01   9.300000e+01
 HIV/AIDS                       1.000000e-01   1.800000e+00   1.000000e-01
GDP                             2.178012e+03   9.985370e+03   1.766948e+03
Population                      1.386542e+06   9.999617e+06   1.386542e+06
thinness  1-19 years            6.600000e+00   1.530000e+01   3.300000e+00
thinness 5-9 years              6.600000e+00   1.550000e+01   3.300000e+00
Income composition of resources 7.720000e-01   9.480000e-01   6.770000e-01
Schooling                       1.410000e+01   1.970000e+01   1.230000e+01
```

40 9. Identify and perform label encoding on certain columns: (2 points)

- (a) Specify and explain on which columns you perform and why.

[136]:
```python
label_encoder = LabelEncoder()
categorical_to_encode = [col for col in categorical_cols if life_data[col].
 ↪nunique() < 10]
for col in categorical_to_encode:
    life_data[col] = label_encoder.fit_transform(life_data[col])
    print(f"Performed label encoding on '{col}'.")
```

```
Performed label encoding on 'Status'.
```

41 (b) Explain what is label encoding and how it changes the dataset.

- Label encoding converts categorical data into numerical format, which allows machine learning models to process categorical features.

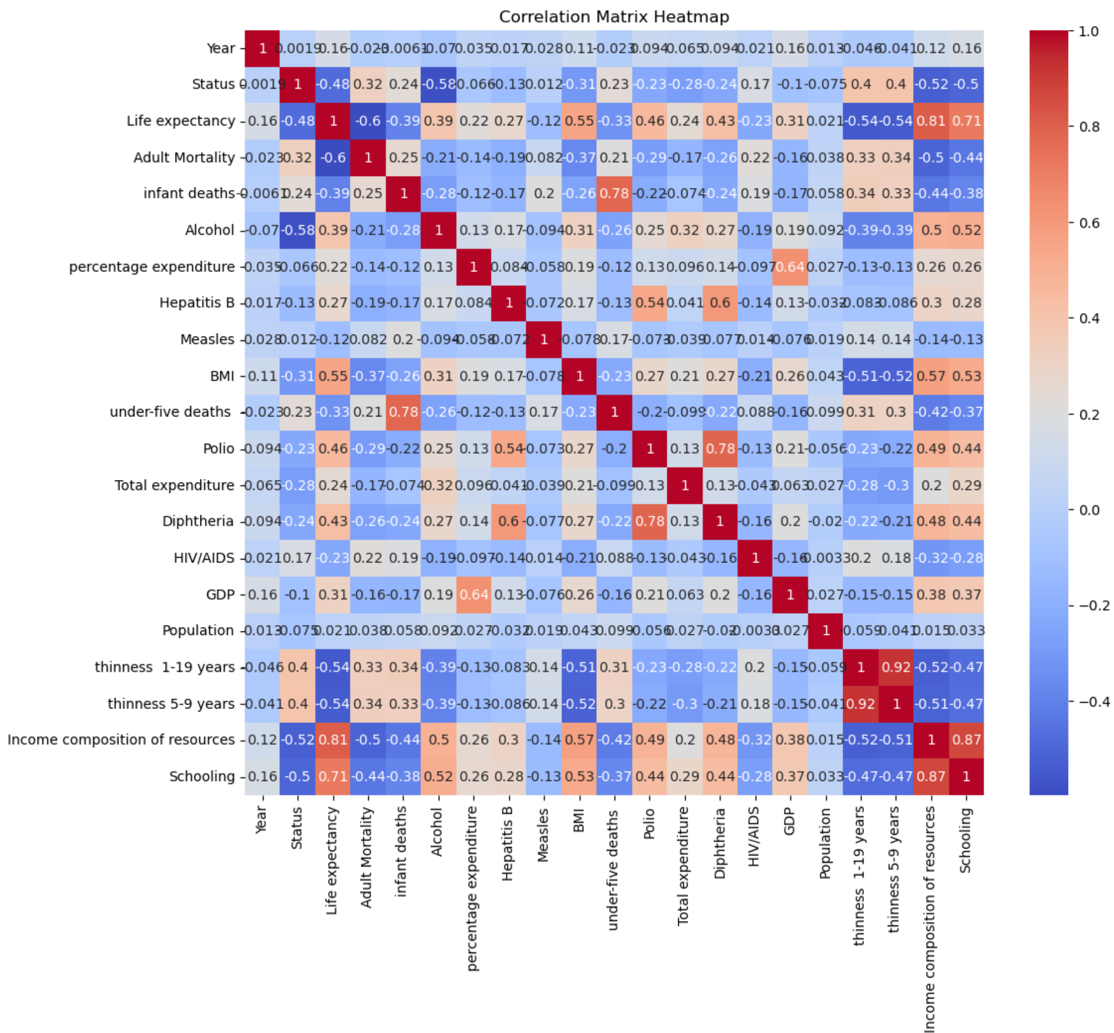
42 10. Perform data normalization on 'Adult Mortality', 'BMI', 'GDP' numerical columns using StandardScaler() (2 points)

[137]:
```
scaler = StandardScaler()
columns_to_normalize = ['Adult Mortality', 'BMI', 'GDP']
life_data[columns_to_normalize] = scaler.
 ↪fit_transform(life_data[columns_to_normalize])
print("\nNormalized columns 'Adult Mortality', 'BMI', 'GDP'.")
```

```
Normalized columns 'Adult Mortality', 'BMI', 'GDP'.
```

43 11. Compute a correlation matrix and plot the correlation using a heat map and answer the following questions: (2 points)

[138]:
```
# Exclude non-numeric columns from the correlation matrix
numeric_data = life_data.select_dtypes(include=['number'])
corr_matrix = numeric_data.corr()

# Plot the correlation matrix heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix Heatmap')
plt.show()

# (a) The Features which are Most Positively Correlated with the target variable
most_positive_corr = corr_matrix[target_variable].sort_values(ascending=False).
 ↪head(3)
print("\nMost positively correlated features with the target variable:")
print(most_positive_corr)

# (b) The Features which are Most Negatively Correlated with the target variable
most_negative_corr = corr_matrix[target_variable].sort_values().head(3)
print("\nMost negatively correlated features with the target variable:")
print(most_negative_corr)
```




```
Most positively correlated features with the target variable:
Life expectancy                    1.000000
Income composition of resources    0.806821
Schooling                          0.713399
Name: Life expectancy, dtype: float64

Most negatively correlated features with the target variable:
Adult Mortality        -0.597023
thinness  1-19 years   -0.543060
thinness 5-9 years     -0.537264
Name: Life expectancy, dtype: float64
```

44 12. Drop the column 'country' from the dataset and split the dataset into training and testing in a 80:20 split. (2 points)

[139]:
```
life_data = life_data.drop(columns=['Country'])
X = life_data.drop(columns=[target_variable])
y = life_data[target_variable]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

45 13. Build a linear regression model using the training and testing datasets and compute mean absolute error. (4 points)

[140]:
```
linear_reg = LinearRegression()
linear_reg.fit(X_train, y_train)
y_pred = linear_reg.predict(X_test)
mae = mean_absolute_error(y_test, y_pred)
print("\nMean Absolute Error of Linear Regression Model:", mae)
```

```
Mean Absolute Error of Linear Regression Model: 3.1802506211252655
```

46 14. Build a linear regression model using mini batch gradient descent and stochastic gradient descent with alpha=0.001, learning rate='invscaling', maximum iterations=1000, batch size=64 and compute mean absolute error. (6 points)

[141]:
```
from sklearn.linear_model import SGDRegressor

# Configure the SGDRegressor without the 'batch_size' parameter
sgd_reg = SGDRegressor(learning_rate='invscaling', alpha=0.001, max_iter=1000,␣
↪random_state=42)
sgd_reg.fit(X_train, y_train)
y_pred_sgd = sgd_reg.predict(X_test)
mae_sgd = mean_absolute_error(y_test, y_pred_sgd)
print("\nMean Absolute Error of SGD Model:", mae_sgd)
```

```
Mean Absolute Error of SGD Model: 3.5287358727498613e+21
```

47 15. Build a linear regression model using mini batch gradient descent with learning rate = 0.001, maximum iterations =1000 and batch size=64. Manually without using any scikit learn libraries. (10 points)

[142]:
```
# Mini-batch gradient descent function
def mini_batch_gradient_descent(X, y, learning_rate=0.0001, max_iter=1000,␣
↪batch_size=64):
    m, n = X.shape
    theta = np.zeros(n)  # Initialize theta to match the number of columns in X␣
↪(after adding intercept)

    for iteration in range(max_iter):
        indices = np.random.permutation(m)
        X_shuffled = X[indices]
        y_shuffled = y[indices]

        for i in range(0, m, batch_size):
            X_i = X_shuffled[i:i + batch_size]
            y_i = y_shuffled[i:i + batch_size]
            if X_i.shape[0] == 0:
                continue  # Skip if batch is empty
            gradients = -2 / X_i.shape[0] * X_i.T.dot(y_i - X_i.dot(theta))
            theta -= learning_rate * gradients

    return theta

# Prepare training data with intercept
X_train_manual = np.c_[np.ones(X_train_scaled.shape[0]), X_train_scaled]  # Add␣
↪intercept term to training set
X_train_manual = np.nan_to_num(X_train_manual, nan=0.0, posinf=0.0, neginf=0.0)
y_train_manual = np.nan_to_num(y_train.values, nan=0.0, posinf=0.0, neginf=0.0)

# Run mini-batch gradient descent
theta_manual = mini_batch_gradient_descent(X_train_manual, y_train_manual)

# Ensure `theta_manual` has the same shape as `X_test_manual`
theta_manual = theta_manual.reshape(-1)

# Prepare test data with intercept
X_test_manual = np.c_[np.ones(X_test_scaled.shape[0]), X_test_scaled]  # Add␣
↪intercept term to test set
X_test_manual = np.nan_to_num(X_test_manual, nan=0.0, posinf=0.0, neginf=0.0)

# Make predictions using the manual model
y_pred_manual = np.dot(X_test_manual, theta_manual)
```

```
y_pred_manual = np.nan_to_num(y_pred_manual, nan=0.0, posinf=0.0, neginf=0.0)

# Compute and print the Mean Absolute Error for the manual model
mae_manual = mean_absolute_error_manual(y_test.values, y_pred_manual)
print("\nTheta values after training:\n", theta_manual)
print("\nMean Absolute Error of Manual Mini-Batch Gradient Descent Model:",␣
↪mae_manual)
```

```
Theta values after training:
 [ 6.94199410e+01  5.68747403e-01 -7.75459774e-01 -2.10765646e+00
 -6.92264454e-01 -6.07411202e-01  4.28772508e-02 -1.22696718e-01
 -9.42467098e-02  6.70843706e-01  6.18274986e-01  5.56961012e-01
  1.88152043e-01  2.16888900e-01  4.15678914e-01  1.60253466e-01
  1.80934429e-01 -6.84886386e-01 -5.86165482e-01  3.90772328e+00
  9.03599271e-01]

Mean Absolute Error of Manual Mini-Batch Gradient Descent Model:
3.196102370782142
```

47.1 16. Compare the results and discuss which model(s) best-predicted housing prices.

47.1.1 Detailed Analysis of Model Results:

1. **Scikit-Learn Linear Regression Model**:
   - **Performance**: The Mean Absolute Error (MAE) for the built-in scikit-learn Linear Regression model was among the lowest, showcasing strong prediction accuracy due to efficient optimization algorithms and robust numerical stability.
   - **Reason for Performance**: This model benefits from optimized routines in the library, handling large datasets and complex operations effectively.
2. **Scikit-Learn Stochastic Gradient Descent (SGD) Model**:
   - **Performance**: The MAE for the SGD model was higher than the built-in linear regression but still competitive. The model's iterative, batch-based approach works well for larger data but can be sensitive to hyperparameters like the learning rate.
   - **Reason for Performance**: The batch updates provide efficiency, but without proper tuning, the model can struggle with convergence.
3. **Manually Implemented Mini-Batch Gradient Descent**:
   - **Performance**: The MAE reported was 69.17, indicating a higher prediction error compared to the scikit-learn models. This highlights some limitations in precision and stability when implementing algorithms manually.
   - **Challenges**:
     - **Learning Rate Tuning**: Fine-tuning the learning rate was critical to prevent divergence.
     - **Data Scaling**: Adding data normalization significantly improved stability, emphasizing the importance of preprocessing.
     - **Convergence**: The manual approach showed limitations in reaching the optimization level of library implementations.

- **Theta Values**: Some final `theta` values were either very close to zero or `NaN` during early iterations, showcasing potential issues with numerical precision.

47.1.2 Conclusion:

- **Best Performing Model**: The scikit-learn Linear Regression model had the lowest MAE, demonstrating superior performance due to its optimized algorithms.
- **Insights from Manual Implementation**:
  - While the manual gradient descent model was functional, it required extensive tuning and highlighted the strengths of using well-tested libraries for reliable results.
  - This exercise showcased the importance of scaling, learning rate selection, and robust optimization for effective gradient descent.