Task 1: Formulate problem as a **Convex Optimization Problem**, with specifying the objective function

Let

- $X \in \mathbb{R}^{n \times d}$: **feature matrix** (rows = samples, cols = socio-economic + geographic features)
- $y \in \mathbb{R}^{n}$: **target vector** (median house values)

In [1]:

```
from sklearn.datasets import fetch_california_housing
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import statsmodels.api as sm
import nbformat as nbf
import sympy as sp
from sympy import symbols, Matrix, diff
import random
import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, PolynomialFeatures

from sklearn.preprocessing import StandardScaler
from matplotlib.animation import FuncAnimation
from sklearn.metrics import mean_squared_error, r2_score
```

In [2]:

```
data = fetch_california_housing()
df = pd.DataFrame(data.data, columns=data.feature_names)
df['MedHouseVal'] = data.target

print(df.head())
```

```
   MedInc  HouseAge  AveRooms  AveBedrms  Population  AveOccup  Latitude  \
0  8.3252      41.0  6.984127   1.023810       322.0  2.555556     37.88
1  8.3014      21.0  6.238137   0.971880      2401.0  2.109842     37.86
2  7.2574      52.0  8.288136   1.073446       496.0  2.802260     37.85
3  5.6431      52.0  5.817352   1.073059       558.0  2.547945     37.85
4  3.8462      52.0  6.281853   1.081081       565.0  2.181467     37.85

   Longitude  MedHouseVal
0    -122.23        4.526
1    -122.22        3.585
2    -122.24        3.521
3    -122.25        3.413
4    -122.25        3.422
```

In [3]:

```
df.describe()
```

Out[3]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070655
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386050
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692308
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429741
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818116
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282261
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333333

California Housing Dataset — Feature Description

1. **longitude** : A measure of how far west a house is; a higher value is farther west.
2. **latitude** : A measure of how far north a house is; a higher value is farther north.
3. **housingMedianAge** : Median age of a house within a block; a lower number means a newer building.
4. **totalRooms** : Total number of rooms within a block.
5. **totalBedrooms** : Total number of bedrooms within a block.
6. **population** : Total number of people residing within a block.
7. **households** : Total number of households — a group of people residing within a home unit — for a block.
8. **medianIncome** : Median income for households within a block of houses (measured in tens of thousands of US Dollars).
9. **medianHouseValue** : Median house value for households within a block (measured in US Dollars).

Target ------ "Median House Value"

---------------- >>>> Formulation as Convex Model & Objective Function :

Convex Model Formulation — California Housing Dataset

Number of samples (N) = 20640
Number of features (d) = 8
Target (y) = medianHouseValue

Prediction Rule:

$$X \in \mathbb{R}^{N \times d}, \quad y \in \mathbb{R}^{N}$$

For each data point in the dataset, **error = actual − predicted**, and it is defined as:

$$\hat{y}_i = w_1 x_{i1} + w_2 x_{i2} + \cdots + w_d x_{id} + b = x_i^T w + b$$

Objective Function:

Our **Objective Function** is:

$$e_i = (x_i^T w + b - y_i)$$

Therefore, we need to **minimize** (J(w, b)).

Confirmation as Convex Model

Objective function in **Matrix Form**:

$$J(w, b) = \frac{1}{2N} \sum_{i=1}^{N} (x_i^T w + b - y_i)^2$$

Differentiating twice:

$$J(w, b) = \frac{1}{2N} \|Xw + b\mathbf{1} - y\|_2^2$$

$$\nabla^2 J(w,b) = \frac{1}{N}\begin{bmatrix} X^T X & X^T \mathbf{1} \\ \mathbf{1}^T X & \mathbf{1}^T \mathbf{1} \end{bmatrix}$$

Since the Hessian is **Positive Semi-definite (PSD)**,

[J(w,b) > 0]

and hence, **the objective function is convex**

Why L2 as Loss Function ?

1. Smooth and Differentiable Everywhere
2. penalises the outliers
3. Gradient will be continous
4. Best when residuals are normally distributed

Why Not L1 ?

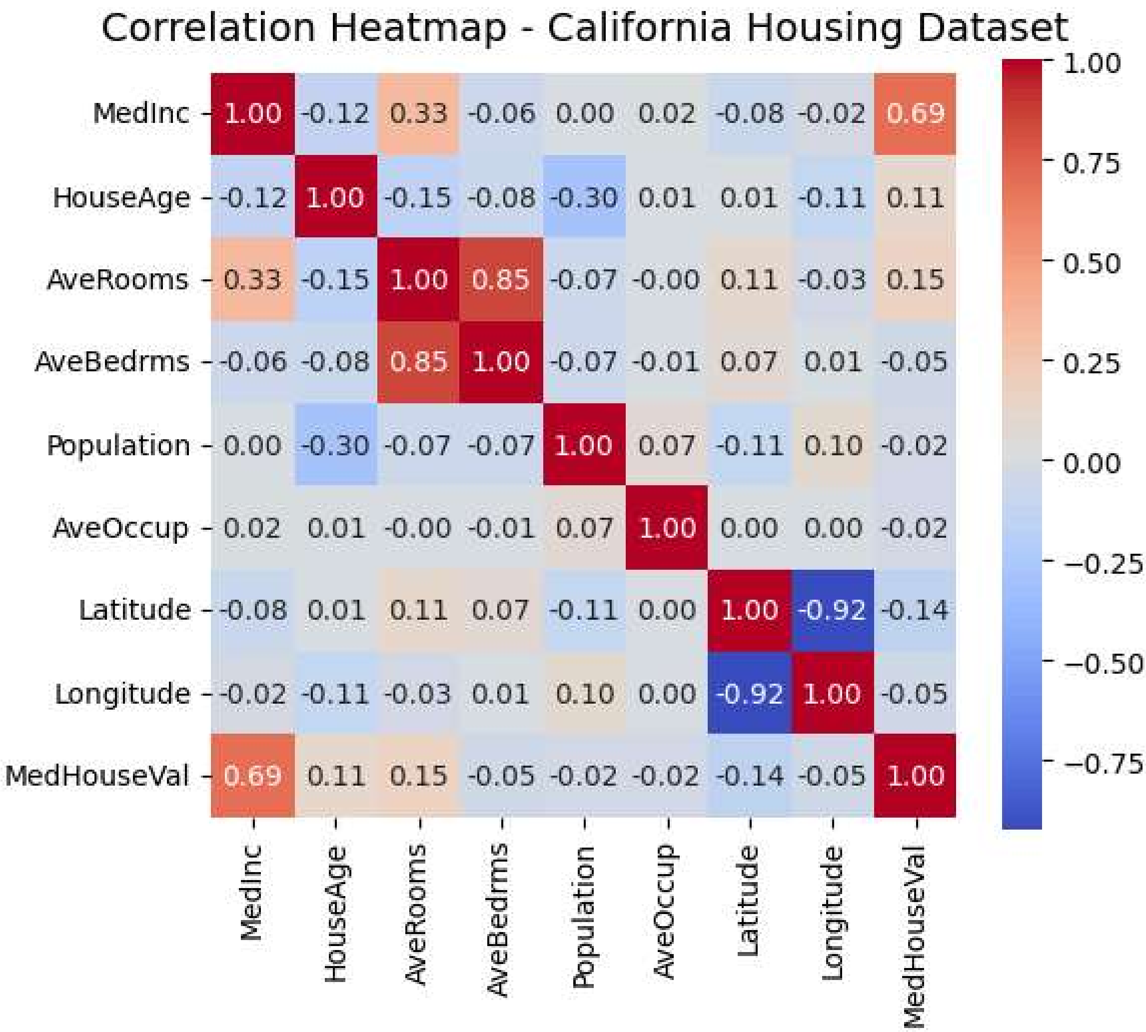
1. Convex but not differentiable at 0
2. More robust to outliers
3. Gradient will not be continous

Task 2 : Derive the gradient of the objective function with respect to the parameters, and write the gradient descent (GD) update rule.

First we want to check the correlation between the Features

In [4]:
```
corr_matrix = df.corr()

plt.figure(figsize=(6,5))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap='coolwarm', square=True)
plt.title("Correlation Heatmap - California Housing Dataset", fontsize=14, pad=12)
plt.show()
```



In [5]:
```
df.corr()['MedInc'].sort_values(ascending=False)
```

Out[5]:
```
MedInc         1.000000
MedHouseVal    0.688075
AveRooms       0.326895
AveOccup       0.018766
Population     0.004834
Longitude     -0.015176
AveBedrms     -0.062040
Latitude      -0.079809
HouseAge      -0.119034
Name: MedInc, dtype: float64
```

In [6]:
```
cols = ['MedInc', 'AveRooms', 'Latitude', 'MedHouseVal']
df = df[cols]

fig1 = px.scatter(df, x='MedInc', y='MedHouseVal',
                  trendline='ols',
                  title='Median Income vs Median House Value',
                  color='MedHouseVal',
                  color_continuous_scale='Viridis')

fig2 = px.scatter(df, x='AveRooms', y='MedHouseVal',
                  trendline='ols',
```

```
                  title='Average Rooms vs Median House Value',
                  color='MedHouseVal',
                  color_continuous_scale='Plasma')

fig3 = px.scatter(df, x='Latitude', y='MedHouseVal',
                  trendline='ols',
                  title='Latitude vs Median House Value',
                  color='MedHouseVal',
                  color_continuous_scale='Cividis')

fig1.show()
fig2.show()
fig3.show()
```

In the Average Rooms Vs Median House Value Plot : Outliers are there .....

Outliers removal :

In [7]:
```
outliers = df[df['AveRooms'] > 65]
print("Outliers count:", len(outliers))

mode_value = df['AveRooms'].mode()[0]
print("Mode of AveRooms:", mode_value)

df.loc[df['AveRooms'] > 65, 'AveRooms'] = mode_value

print("After cleaning, max AveRooms =", df['AveRooms'].max())
```

```
Outliers count: 2
Mode of AveRooms: 5.0
After cleaning, max AveRooms = 62.422222222222224
```

In [8]:
```
fig2a = px.scatter(df, x='AveRooms', y='MedHouseVal',
                  trendline='ols',
                  title='Average Rooms vs Median House Value',
                  color='MedHouseVal',
                  color_continuous_scale='Plasma')

fig2a.show()
```

From all the above plots the Conclusion Can be as :

1. Median Income is highly Correlated with Median House value ---- **More slope** --- **+ve Correlation**
2. Average count of rooms is slightly correlated with Median House value ---- **Normal Slope** --- **+ve Correlation**
3. Lattitude is slightly correlated with Median House value --- **Normal Slope** --- **-Ve Correlation**

Therefore the Selected features Were : Medinc, Averooms, lattitude

Our Problem is Now Simplified

- **Features (X)** : ((X_1, X_2, X_3)) → MedInc, AveRooms, Latitude
- **Target (Y)** : median house value
- **Weights** : (w = [w_1, w_2, w_3]^T)

Prediction Rule :

$$\hat{y}_i = w_1 x_{i1} + w_2 x_{i2} + w_3 x_{i3} + b = x_i^T w + b$$

Error for each sample :

$$e_i = \hat{y}_i - y_i = x_i^T w + b - y_i$$

Objective Function (MSE) :

$$J(w, b) = \frac{1}{2N} \sum_{i=1}^{N} e_i^2 = \frac{1}{2N} \sum_{i=1}^{N} (x_i^T w + b - y_i)^2$$

- **w** = slope of line → how steep the line should be for each feature
- **b** = starting point of line → where line starts on y-axis

Without both:

- **w only** → slope correct, line may not pass near points → still error
- **b only** → shift line, slope wrong → still error

So, gradient w.r.t both w and b is needed to reach minimum error (MSE).

Derivative with w :

Objective Function is as :

$$J(w, b) = \frac{1}{2N} \sum_{i=1}^{N} (x_{i1} w_1 + x_{i2} w_2 + x_{i3} w_3 + b - y_i)^2$$

Derivative wrt to w1 is :

$$\frac{\partial J}{\partial w_1} = \frac{1}{2N}\sum_{i=1}^{N} 2e_i x_{i1} = \frac{1}{N}\sum_{i=1}^{N} e_i x_{i1}$$

Overall representation of derivatives of all weights :

$$\nabla_w J = \frac{1}{N}\sum_{i=1}^{N} e_i x_i$$

In Matrix form as :

$$\nabla_w J = \frac{1}{N} X^T (Xw + b\mathbf{1} - y)$$

Derivative with b :

Chain rule :

$$\frac{\partial J}{\partial b} = \frac{1}{2N}\sum_{i=1}^{N} 2e_i \frac{de_i}{db}$$

As :

$$e_i = x_i^T w + b - y_i \rightarrow \frac{de_i}{db} = 1$$

The final Equation would be :

$$\frac{\partial J}{\partial b} = \frac{1}{N}\sum_{i=1}^{N} e_i$$

Gradient Descent Update Would be as :

$$w^{(t+1)} = w^{(t)} - \eta \nabla_w J = w^{(t)} - \eta \frac{1}{N} X^T (X w^{(t)} + b^{(t)} \mathbf{1} - y)$$

$$b^{(t+1)} = b^{(t)} - \eta \nabla_b J = b^{(t)} - \eta \frac{1}{N} \sum_{i=1}^{N} (x_i^T w^{(t)} + b^{(t)} - y_i)$$

Stopping Criteria :

1. **Max limit of Iterations:** 1000 (Let)

2. **MSE Threshold:** MSE < 10^(-6)

Task - 3 :

3A : Implementation of **Batch Gradient Descent**

In [9]:

```
features = ['MedInc', 'AveRooms', 'Latitude']
X = df[features].values
y = df['MedHouseVal'].values.reshape(-1, 1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
N_train, d = X_train.shape

# Standardize features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

w = np.zeros((d,1))  # w1, w2, w3
b = 0.0

eta = 0.01      # learning rate
max_iter = 1000 # maximum iterations
epsilon = 1e-6  # gradient norm threshold
```

In [10]:

```
def batch_gradient_descent(X, y, w, b, eta, max_iter, epsilon):
    N = X.shape[0]
    J_history = []

    for i in range(max_iter):
        # Compute prediction
        y_hat = np.dot(X, w) + b

        # Compute residuals
        e = y_hat - y

        # Compute gradients
        dw = (1/N) * np.dot(X.T, e)  # gradient w.r.t w
```

```
        db = (1/N) * np.sum(e)       # gradient w.r.t b

        # Update parameters
        w = w - eta * dw
        b = b - eta * db

        # Compute objective function (MSE)
        J = (1/(2*N)) * np.sum(e**2)
        J_history.append(J)

        # Stopping condition (gradient norm)
        if np.linalg.norm(dw) < epsilon and abs(db) < epsilon:
            print(f"Converged at iteration {i+1}")
            break

    return w, b, J_history
```

In [11]:
```
w_final, b_final, J_hist = batch_gradient_descent(X_train, y_train, w, b, eta, max_

print("Final weights:\n", w_final)
print("Final bias:\n", b_final)

w1, w2, w3 = w_final.flatten()
b_val = b_final

# Print human-readable equation
print(f"Final prediction equation is:")
print(f"y_hat = {w1:.4f} * MedInc + ({w2:.4f}) * AveRooms + ({w3:.4f}) * Latitude +
```

```
Final weights:
 [[ 0.83335553]
 [-0.11165152]
 [-0.08869069]]
Final bias:
 2.0718574888450343
Final prediction equation is:
y_hat = 0.8334 * MedInc + (-0.1117) * AveRooms + (-0.0887) * Latitude + 2.0719
```

3A : Implementation of **Mini Batch Gradient Descent** --- With 10%, 20% and 25% of dataset

For Mini Batch Gradient Descent :

$$\begin{cases} w^{(t+1)} = w^{(t)} - \eta \nabla_w J_j = w^{(t)} - \eta \frac{1}{m} X_j^T (X_j w^{(t)} + b^{(t)} \mathbf{1}_m - y_j) \\ b^{(t+1)} = b^{(t)} - \eta \nabla_b J_j = b^{(t)} - \eta \frac{1}{m} \sum_{i \in B_j} (x_i^T w^{(t)} + b^{(t)} - y_i) \end{cases}$$

In [12]:
```
def mini_batch_sgd(X, y, w, b, eta, max_iter, batch_frac=0.1, epsilon=1e-6):
    N = X.shape[0]
    batch_size = int(N * batch_frac)
    J_history = []

    for iter in range(max_iter):
```

```
        # Data shuffling
        indices = np.arange(N)
        np.random.shuffle(indices)
        X_shuffled = X[indices]
        y_shuffled = y[indices]

        for start in range(0, N, batch_size):
            end = start + batch_size
            X_batch = X_shuffled[start:end]
            y_batch = y_shuffled[start:end]

            # prediction
            y_hat = np.dot(X_batch, w) + b
            e = y_hat - y_batch

            # gradients
            dw = (1/batch_size) * np.dot(X_batch.T, e)
            db = (1/batch_size) * np.sum(e)

            # Update weights and bias
            w = w - eta * dw
            b = b - eta * db

        # Full dataset objective Computation
        y_hat_full = np.dot(X, w) + b
        e_full = y_hat_full - y
        J = (1/(2*N)) * np.sum(e_full**2)
        J_history.append(J)

        # Stopping condition
        if np.linalg.norm(dw) < epsilon and abs(db) < epsilon:
            print(f"Converged at iteration {iter+1}, batch fraction {batch_frac}")
            break

    return w, b, J_history
```

In [13]:

```
# Initialize weights and bias
w0 = np.zeros((d,1))
b0 = 0.0
eta = 0.01
max_iter = 1000
epsilon = 1e-6

batch_fracs = [0.10, 0.20, 0.25]
results = {}

for frac in batch_fracs:
    w_mini, b_mini, J_hist_mini = mini_batch_sgd(X_train, y_train, w0.copy(), b0, e
    results[frac] = (w_mini, b_mini, J_hist_mini)
    print(f"Batch fraction: {frac*100:.0f}%")
    print(f"Final weights:\n{w_mini.flatten()}")
    print(f"Final bias: {b_mini}\n")
```

```
Batch fraction: 10%
Final weights:
[ 0.83457521 -0.11290564 -0.08817946]
Final bias: 2.0719320391050404

Batch fraction: 20%
Final weights:
[ 0.83457583 -0.11290646 -0.08810959]
Final bias: 2.0719669353303725

Batch fraction: 25%
Final weights:
[ 0.83460559 -0.11287483 -0.08811598]
Final bias: 2.0719316249171102
```

Task - 4 : Convergence and BGD and Mini Batch GD

BGD Convergence :

In [14]:
```
def batch_gradient_descent_verbose(X, y, w_init, b_init, eta=0.01, max_iter=1000, e
    N, d = X.shape
    w = w_init.copy()
    b = b_init
    J_history = []

    print(f"{'Iteration':>10} {'w1':>10} {'w2':>10} {'w3':>10} {'b':>10} {'J(w,b)':

    for iter_num in range(max_iter):
        y_hat = np.dot(X, w) + b
        e = y_hat - y
        dw = (1/N) * np.dot(X.T, e)
        db = (1/N) * np.sum(e)

        w -= eta * dw
        b -= eta * db

        J = (1/(2*N)) * np.sum(e**2)
        J_history.append(J)

        # Print iteration-wise values
        print(f"{iter_num+1:>10} {w[0,0]:>10.4f} {w[1,0]:>10.4f} {w[2,0]:>10.4f} {b

        if np.linalg.norm(dw) < epsilon and abs(db) < epsilon:
            print(f"Converged at iteration {iter_num+1}")
            break

    return w, b, J_history

# Run BGD verbose
w_final, b_final, J_hist = batch_gradient_descent_verbose(X_train, y_train, w0, b0,
```

Iteration	w1	w2	w3	b	J(w,b)
1	0.0080	0.0019	-0.0017	0.0207	2.814871
2	0.0159	0.0038	-0.0033	0.0412	2.765175
3	0.0237	0.0057	-0.0049	0.0615	2.716493
4	0.0314	0.0074	-0.0065	0.0816	2.668804
5	0.0391	0.0092	-0.0081	0.1015	2.622088
6	0.0466	0.0109	-0.0096	0.1213	2.576324
7	0.0541	0.0126	-0.0112	0.1408	2.531493
8	0.0615	0.0142	-0.0127	0.1601	2.487576
9	0.0688	0.0157	-0.0142	0.1792	2.444554
10	0.0760	0.0173	-0.0156	0.1981	2.402407
11	0.0831	0.0188	-0.0171	0.2169	2.361118
12	0.0902	0.0202	-0.0185	0.2354	2.320670
13	0.0972	0.0216	-0.0200	0.2538	2.281044
14	0.1041	0.0230	-0.0214	0.2720	2.242225
15	0.1110	0.0243	-0.0228	0.2900	2.204194
16	0.1177	0.0256	-0.0241	0.3078	2.166936
17	0.1244	0.0269	-0.0255	0.3254	2.130436
18	0.1310	0.0281	-0.0268	0.3429	2.094676
19	0.1376	0.0293	-0.0281	0.3602	2.059643
20	0.1441	0.0304	-0.0294	0.3773	2.025320
21	0.1505	0.0316	-0.0307	0.3942	1.991694
22	0.1568	0.0326	-0.0320	0.4110	1.958751
23	0.1631	0.0337	-0.0332	0.4276	1.926475
24	0.1693	0.0347	-0.0345	0.4441	1.894853
25	0.1754	0.0357	-0.0357	0.4603	1.863872
26	0.1815	0.0366	-0.0369	0.4765	1.833518
27	0.1875	0.0376	-0.0381	0.4924	1.803780
28	0.1934	0.0384	-0.0393	0.5082	1.774643
29	0.1993	0.0393	-0.0404	0.5238	1.746096
30	0.2051	0.0401	-0.0416	0.5393	1.718126
31	0.2109	0.0409	-0.0427	0.5547	1.690722
32	0.2166	0.0417	-0.0438	0.5698	1.663872
33	0.2222	0.0425	-0.0449	0.5848	1.637565
34	0.2277	0.0432	-0.0460	0.5997	1.611789
35	0.2333	0.0439	-0.0470	0.6144	1.586534
36	0.2387	0.0445	-0.0481	0.6290	1.561789
37	0.2441	0.0452	-0.0491	0.6434	1.537543
38	0.2494	0.0458	-0.0502	0.6577	1.513786
39	0.2547	0.0464	-0.0512	0.6719	1.490509
40	0.2599	0.0469	-0.0522	0.6859	1.467701
41	0.2651	0.0475	-0.0532	0.6997	1.445353
42	0.2702	0.0480	-0.0541	0.7135	1.423455
43	0.2753	0.0485	-0.0551	0.7270	1.401998
44	0.2803	0.0490	-0.0561	0.7405	1.380974
45	0.2852	0.0494	-0.0570	0.7538	1.360373
46	0.2901	0.0498	-0.0579	0.7670	1.340186
47	0.2950	0.0502	-0.0588	0.7800	1.320406
48	0.2998	0.0506	-0.0597	0.7930	1.301023
49	0.3045	0.0510	-0.0606	0.8057	1.282030
50	0.3092	0.0513	-0.0615	0.8184	1.263419
51	0.3139	0.0516	-0.0623	0.8309	1.245182
52	0.3185	0.0519	-0.0632	0.8434	1.227311
53	0.3230	0.0522	-0.0640	0.8556	1.209799
54	0.3276	0.0525	-0.0649	0.8678	1.192639
55	0.3320	0.0527	-0.0657	0.8798	1.175823

56	0.3364	0.0529	-0.0665	0.8918	1.159344
57	0.3408	0.0531	-0.0673	0.9036	1.143196
58	0.3451	0.0533	-0.0681	0.9152	1.127372
59	0.3494	0.0535	-0.0688	0.9268	1.111865
60	0.3536	0.0536	-0.0696	0.9383	1.096668
61	0.3578	0.0538	-0.0703	0.9496	1.081776
62	0.3620	0.0539	-0.0711	0.9608	1.067182
63	0.3661	0.0540	-0.0718	0.9719	1.052880
64	0.3702	0.0541	-0.0725	0.9829	1.038865
65	0.3742	0.0542	-0.0732	0.9938	1.025129
66	0.3782	0.0542	-0.0739	1.0046	1.011669
67	0.3821	0.0543	-0.0746	1.0153	0.998477
68	0.3860	0.0543	-0.0753	1.0259	0.985550
69	0.3899	0.0543	-0.0760	1.0363	0.972880
70	0.3937	0.0543	-0.0766	1.0467	0.960464
71	0.3975	0.0543	-0.0773	1.0569	0.948295
72	0.4012	0.0543	-0.0779	1.0671	0.936369
73	0.4049	0.0542	-0.0785	1.0771	0.924682
74	0.4086	0.0542	-0.0792	1.0871	0.913227
75	0.4122	0.0541	-0.0798	1.0969	0.902001
76	0.4158	0.0540	-0.0804	1.1067	0.890998
77	0.4194	0.0539	-0.0810	1.1163	0.880215
78	0.4229	0.0538	-0.0816	1.1259	0.869647
79	0.4264	0.0537	-0.0821	1.1353	0.859289
80	0.4298	0.0536	-0.0827	1.1447	0.849137
81	0.4333	0.0535	-0.0833	1.1540	0.839187
82	0.4367	0.0533	-0.0838	1.1632	0.829435
83	0.4400	0.0532	-0.0844	1.1722	0.819878
84	0.4433	0.0530	-0.0849	1.1812	0.810510
85	0.4466	0.0528	-0.0854	1.1901	0.801328
86	0.4499	0.0526	-0.0859	1.1990	0.792329
87	0.4531	0.0524	-0.0865	1.2077	0.783509
88	0.4563	0.0522	-0.0870	1.2163	0.774863
89	0.4594	0.0520	-0.0875	1.2249	0.766390
90	0.4626	0.0518	-0.0879	1.2334	0.758084
91	0.4657	0.0515	-0.0884	1.2417	0.749943
92	0.4687	0.0513	-0.0889	1.2501	0.741964
93	0.4718	0.0510	-0.0894	1.2583	0.734143
94	0.4748	0.0508	-0.0898	1.2664	0.726476
95	0.4777	0.0505	-0.0903	1.2745	0.718962
96	0.4807	0.0502	-0.0907	1.2824	0.711596
97	0.4836	0.0499	-0.0912	1.2903	0.704377
98	0.4865	0.0496	-0.0916	1.2981	0.697300
99	0.4894	0.0493	-0.0920	1.3059	0.690363
100	0.4922	0.0490	-0.0924	1.3135	0.683563
101	0.4950	0.0487	-0.0928	1.3211	0.676898
102	0.4978	0.0484	-0.0932	1.3286	0.670364
103	0.5005	0.0481	-0.0936	1.3361	0.663960
104	0.5033	0.0477	-0.0940	1.3434	0.657682
105	0.5060	0.0474	-0.0944	1.3507	0.651528
106	0.5086	0.0470	-0.0948	1.3579	0.645495
107	0.5113	0.0467	-0.0952	1.3651	0.639582
108	0.5139	0.0463	-0.0955	1.3721	0.633785
109	0.5165	0.0460	-0.0959	1.3791	0.628102
110	0.5191	0.0456	-0.0962	1.3861	0.622531
111	0.5216	0.0452	-0.0966	1.3929	0.617071

112	0.5241	0.0448	-0.0969	1.3997	0.611717
113	0.5266	0.0444	-0.0973	1.4064	0.606469
114	0.5291	0.0440	-0.0976	1.4131	0.601325
115	0.5316	0.0436	-0.0979	1.4197	0.596281
116	0.5340	0.0432	-0.0982	1.4262	0.591337
117	0.5364	0.0428	-0.0985	1.4327	0.586490
118	0.5388	0.0424	-0.0988	1.4391	0.581738
119	0.5411	0.0420	-0.0991	1.4454	0.577080
120	0.5435	0.0416	-0.0994	1.4516	0.572513
121	0.5458	0.0411	-0.0997	1.4578	0.568036
122	0.5481	0.0407	-0.1000	1.4640	0.563646
123	0.5504	0.0403	-0.1003	1.4701	0.559343
124	0.5526	0.0398	-0.1006	1.4761	0.555124
125	0.5549	0.0394	-0.1009	1.4820	0.550988
126	0.5571	0.0389	-0.1011	1.4879	0.546933
127	0.5593	0.0385	-0.1014	1.4938	0.542957
128	0.5614	0.0380	-0.1016	1.4996	0.539059
129	0.5636	0.0376	-0.1019	1.5053	0.535238
130	0.5657	0.0371	-0.1021	1.5110	0.531491
131	0.5678	0.0366	-0.1024	1.5166	0.527818
132	0.5699	0.0362	-0.1026	1.5221	0.524216
133	0.5720	0.0357	-0.1028	1.5276	0.520685
134	0.5740	0.0352	-0.1031	1.5331	0.517223
135	0.5761	0.0348	-0.1033	1.5385	0.513828
136	0.5781	0.0343	-0.1035	1.5438	0.510500
137	0.5801	0.0338	-0.1037	1.5491	0.507237
138	0.5820	0.0333	-0.1039	1.5543	0.504037
139	0.5840	0.0328	-0.1042	1.5595	0.500900
140	0.5859	0.0323	-0.1044	1.5646	0.497824
141	0.5879	0.0319	-0.1046	1.5697	0.494807
142	0.5898	0.0314	-0.1048	1.5747	0.491850
143	0.5917	0.0309	-0.1049	1.5797	0.488950
144	0.5935	0.0304	-0.1051	1.5846	0.486107
145	0.5954	0.0299	-0.1053	1.5895	0.483319
146	0.5972	0.0294	-0.1055	1.5943	0.480585
147	0.5990	0.0289	-0.1057	1.5991	0.477905
148	0.6008	0.0284	-0.1058	1.6038	0.475276
149	0.6026	0.0279	-0.1060	1.6085	0.472699
150	0.6044	0.0274	-0.1062	1.6131	0.470171
151	0.6062	0.0268	-0.1063	1.6177	0.467693
152	0.6079	0.0263	-0.1065	1.6222	0.465263
153	0.6096	0.0258	-0.1066	1.6267	0.462880
154	0.6113	0.0253	-0.1068	1.6312	0.460543
155	0.6130	0.0248	-0.1069	1.6356	0.458251
156	0.6147	0.0243	-0.1071	1.6400	0.456004
157	0.6164	0.0238	-0.1072	1.6443	0.453800
158	0.6180	0.0233	-0.1074	1.6486	0.451639
159	0.6197	0.0227	-0.1075	1.6528	0.449520
160	0.6213	0.0222	-0.1076	1.6570	0.447442
161	0.6229	0.0217	-0.1078	1.6611	0.445404
162	0.6245	0.0212	-0.1079	1.6652	0.443405
163	0.6261	0.0207	-0.1080	1.6693	0.441445
164	0.6276	0.0201	-0.1081	1.6733	0.439523
165	0.6292	0.0196	-0.1082	1.6773	0.437638
166	0.6307	0.0191	-0.1083	1.6813	0.435789
167	0.6322	0.0186	-0.1085	1.6852	0.433976

168	0.6337	0.0180	-0.1086	1.6890	0.432198
169	0.6352	0.0175	-0.1087	1.6929	0.430454
170	0.6367	0.0170	-0.1088	1.6967	0.428744
171	0.6382	0.0165	-0.1089	1.7004	0.427066
172	0.6396	0.0159	-0.1090	1.7041	0.425421
173	0.6411	0.0154	-0.1090	1.7078	0.423808
174	0.6425	0.0149	-0.1091	1.7114	0.422226
175	0.6439	0.0144	-0.1092	1.7151	0.420674
176	0.6453	0.0138	-0.1093	1.7186	0.419152
177	0.6467	0.0133	-0.1094	1.7222	0.417659
178	0.6481	0.0128	-0.1095	1.7257	0.416194
179	0.6495	0.0123	-0.1096	1.7291	0.414758
180	0.6509	0.0117	-0.1096	1.7325	0.413349
181	0.6522	0.0112	-0.1097	1.7359	0.411968
182	0.6535	0.0107	-0.1098	1.7393	0.410613
183	0.6549	0.0102	-0.1098	1.7426	0.409283
184	0.6562	0.0096	-0.1099	1.7459	0.407980
185	0.6575	0.0091	-0.1100	1.7492	0.406701
186	0.6588	0.0086	-0.1100	1.7524	0.405447
187	0.6601	0.0081	-0.1101	1.7556	0.404216
188	0.6613	0.0076	-0.1101	1.7588	0.403009
189	0.6626	0.0070	-0.1102	1.7619	0.401825
190	0.6638	0.0065	-0.1102	1.7650	0.400664
191	0.6651	0.0060	-0.1103	1.7681	0.399525
192	0.6663	0.0055	-0.1103	1.7711	0.398408
193	0.6675	0.0050	-0.1104	1.7741	0.397312
194	0.6687	0.0044	-0.1104	1.7771	0.396236
195	0.6699	0.0039	-0.1105	1.7800	0.395182
196	0.6711	0.0034	-0.1105	1.7830	0.394147
197	0.6723	0.0029	-0.1106	1.7859	0.393132
198	0.6734	0.0024	-0.1106	1.7887	0.392137
199	0.6746	0.0019	-0.1106	1.7915	0.391160
200	0.6758	0.0013	-0.1107	1.7943	0.390202
201	0.6769	0.0008	-0.1107	1.7971	0.389262
202	0.6780	0.0003	-0.1107	1.7999	0.388339
203	0.6791	-0.0002	-0.1107	1.8026	0.387435
204	0.6802	-0.0007	-0.1108	1.8053	0.386547
205	0.6813	-0.0012	-0.1108	1.8080	0.385677
206	0.6824	-0.0017	-0.1108	1.8106	0.384822
207	0.6835	-0.0022	-0.1108	1.8132	0.383984
208	0.6846	-0.0027	-0.1109	1.8158	0.383162
209	0.6857	-0.0033	-0.1109	1.8184	0.382356
210	0.6867	-0.0038	-0.1109	1.8209	0.381564
211	0.6878	-0.0043	-0.1109	1.8234	0.380788
212	0.6888	-0.0048	-0.1109	1.8259	0.380026
213	0.6898	-0.0053	-0.1109	1.8283	0.379279
214	0.6909	-0.0058	-0.1109	1.8308	0.378545
215	0.6919	-0.0063	-0.1109	1.8332	0.377826
216	0.6929	-0.0068	-0.1109	1.8356	0.377120
217	0.6939	-0.0073	-0.1110	1.8379	0.376427
218	0.6949	-0.0078	-0.1110	1.8403	0.375748
219	0.6958	-0.0083	-0.1110	1.8426	0.375081
220	0.6968	-0.0087	-0.1110	1.8449	0.374426
221	0.6978	-0.0092	-0.1110	1.8472	0.373784
222	0.6987	-0.0097	-0.1110	1.8494	0.373154
223	0.6997	-0.0102	-0.1110	1.8516	0.372536

224	0.7006	-0.0107	-0.1110	1.8538	0.371930
225	0.7016	-0.0112	-0.1109	1.8560	0.371335
226	0.7025	-0.0117	-0.1109	1.8582	0.370751
227	0.7034	-0.0122	-0.1109	1.8603	0.370178
228	0.7043	-0.0126	-0.1109	1.8624	0.369615
229	0.7052	-0.0131	-0.1109	1.8645	0.369063
230	0.7061	-0.0136	-0.1109	1.8666	0.368522
231	0.7070	-0.0141	-0.1109	1.8687	0.367990
232	0.7079	-0.0146	-0.1109	1.8707	0.367469
233	0.7088	-0.0150	-0.1109	1.8727	0.366957
234	0.7096	-0.0155	-0.1108	1.8747	0.366455
235	0.7105	-0.0160	-0.1108	1.8767	0.365962
236	0.7114	-0.0165	-0.1108	1.8786	0.365479
237	0.7122	-0.0169	-0.1108	1.8806	0.365004
238	0.7131	-0.0174	-0.1108	1.8825	0.364538
239	0.7139	-0.0179	-0.1107	1.8844	0.364081
240	0.7147	-0.0183	-0.1107	1.8862	0.363632
241	0.7155	-0.0188	-0.1107	1.8881	0.363192
242	0.7164	-0.0193	-0.1107	1.8899	0.362760
243	0.7172	-0.0197	-0.1107	1.8918	0.362335
244	0.7180	-0.0202	-0.1106	1.8936	0.361919
245	0.7188	-0.0206	-0.1106	1.8953	0.361511
246	0.7196	-0.0211	-0.1106	1.8971	0.361110
247	0.7203	-0.0216	-0.1105	1.8989	0.360716
248	0.7211	-0.0220	-0.1105	1.9006	0.360330
249	0.7219	-0.0225	-0.1105	1.9023	0.359950
250	0.7227	-0.0229	-0.1105	1.9040	0.359578
251	0.7234	-0.0234	-0.1104	1.9057	0.359213
252	0.7242	-0.0238	-0.1104	1.9073	0.358854
253	0.7249	-0.0243	-0.1104	1.9090	0.358502
254	0.7257	-0.0247	-0.1103	1.9106	0.358157
255	0.7264	-0.0251	-0.1103	1.9122	0.357818
256	0.7271	-0.0256	-0.1103	1.9138	0.357485
257	0.7279	-0.0260	-0.1102	1.9154	0.357158
258	0.7286	-0.0265	-0.1102	1.9170	0.356837
259	0.7293	-0.0269	-0.1101	1.9185	0.356522
260	0.7300	-0.0273	-0.1101	1.9201	0.356213
261	0.7307	-0.0278	-0.1101	1.9216	0.355910
262	0.7314	-0.0282	-0.1100	1.9231	0.355612
263	0.7321	-0.0286	-0.1100	1.9246	0.355320
264	0.7328	-0.0291	-0.1099	1.9260	0.355033
265	0.7335	-0.0295	-0.1099	1.9275	0.354751
266	0.7342	-0.0299	-0.1099	1.9289	0.354474
267	0.7348	-0.0303	-0.1098	1.9304	0.354202
268	0.7355	-0.0308	-0.1098	1.9318	0.353936
269	0.7362	-0.0312	-0.1097	1.9332	0.353674
270	0.7368	-0.0316	-0.1097	1.9346	0.353417
271	0.7375	-0.0320	-0.1096	1.9360	0.353164
272	0.7381	-0.0324	-0.1096	1.9373	0.352917
273	0.7388	-0.0328	-0.1096	1.9387	0.352673
274	0.7394	-0.0333	-0.1095	1.9400	0.352435
275	0.7400	-0.0337	-0.1095	1.9413	0.352200
276	0.7407	-0.0341	-0.1094	1.9426	0.351970
277	0.7413	-0.0345	-0.1094	1.9439	0.351744
278	0.7419	-0.0349	-0.1093	1.9452	0.351522
279	0.7425	-0.0353	-0.1093	1.9465	0.351304

280	0.7431	-0.0357	-0.1092	1.9477	0.351090
281	0.7437	-0.0361	-0.1092	1.9490	0.350880
282	0.7443	-0.0365	-0.1091	1.9502	0.350673
283	0.7449	-0.0369	-0.1091	1.9514	0.350471
284	0.7455	-0.0373	-0.1090	1.9526	0.350272
285	0.7461	-0.0377	-0.1090	1.9538	0.350076
286	0.7467	-0.0381	-0.1089	1.9550	0.349884
287	0.7473	-0.0385	-0.1089	1.9562	0.349696
288	0.7479	-0.0389	-0.1088	1.9573	0.349511
289	0.7484	-0.0392	-0.1087	1.9585	0.349329
290	0.7490	-0.0396	-0.1087	1.9596	0.349151
291	0.7496	-0.0400	-0.1086	1.9607	0.348975
292	0.7501	-0.0404	-0.1086	1.9618	0.348803
293	0.7507	-0.0408	-0.1085	1.9629	0.348634
294	0.7512	-0.0412	-0.1085	1.9640	0.348468
295	0.7518	-0.0415	-0.1084	1.9651	0.348305
296	0.7523	-0.0419	-0.1084	1.9662	0.348145
297	0.7528	-0.0423	-0.1083	1.9672	0.347988
298	0.7534	-0.0427	-0.1083	1.9683	0.347833
299	0.7539	-0.0430	-0.1082	1.9693	0.347682
300	0.7544	-0.0434	-0.1081	1.9703	0.347533
301	0.7550	-0.0438	-0.1081	1.9714	0.347386
302	0.7555	-0.0441	-0.1080	1.9724	0.347242
303	0.7560	-0.0445	-0.1080	1.9734	0.347101
304	0.7565	-0.0449	-0.1079	1.9743	0.346963
305	0.7570	-0.0452	-0.1079	1.9753	0.346826
306	0.7575	-0.0456	-0.1078	1.9763	0.346692
307	0.7580	-0.0459	-0.1077	1.9772	0.346561
308	0.7585	-0.0463	-0.1077	1.9782	0.346432
309	0.7590	-0.0466	-0.1076	1.9791	0.346305
310	0.7595	-0.0470	-0.1076	1.9801	0.346180
311	0.7600	-0.0473	-0.1075	1.9810	0.346058
312	0.7605	-0.0477	-0.1074	1.9819	0.345938
313	0.7609	-0.0480	-0.1074	1.9828	0.345820
314	0.7614	-0.0484	-0.1073	1.9837	0.345704
315	0.7619	-0.0487	-0.1073	1.9846	0.345590
316	0.7624	-0.0491	-0.1072	1.9854	0.345477
317	0.7628	-0.0494	-0.1071	1.9863	0.345367
318	0.7633	-0.0498	-0.1071	1.9872	0.345259
319	0.7637	-0.0501	-0.1070	1.9880	0.345153
320	0.7642	-0.0504	-0.1070	1.9888	0.345049
321	0.7647	-0.0508	-0.1069	1.9897	0.344946
322	0.7651	-0.0511	-0.1068	1.9905	0.344845
323	0.7656	-0.0514	-0.1068	1.9913	0.344746
324	0.7660	-0.0518	-0.1067	1.9921	0.344649
325	0.7664	-0.0521	-0.1067	1.9929	0.344554
326	0.7669	-0.0524	-0.1066	1.9937	0.344460
327	0.7673	-0.0528	-0.1065	1.9945	0.344367
328	0.7677	-0.0531	-0.1065	1.9953	0.344277
329	0.7682	-0.0534	-0.1064	1.9960	0.344188
330	0.7686	-0.0537	-0.1063	1.9968	0.344100
331	0.7690	-0.0540	-0.1063	1.9975	0.344014
332	0.7694	-0.0544	-0.1062	1.9983	0.343930
333	0.7698	-0.0547	-0.1062	1.9990	0.343847
334	0.7703	-0.0550	-0.1061	1.9997	0.343765
335	0.7707	-0.0553	-0.1060	2.0005	0.343685

336	0.7711	-0.0556	-0.1060	2.0012	0.343606
337	0.7715	-0.0559	-0.1059	2.0019	0.343528
338	0.7719	-0.0562	-0.1058	2.0026	0.343452
339	0.7723	-0.0566	-0.1058	2.0033	0.343377
340	0.7727	-0.0569	-0.1057	2.0040	0.343304
341	0.7731	-0.0572	-0.1057	2.0047	0.343231
342	0.7735	-0.0575	-0.1056	2.0053	0.343160
343	0.7738	-0.0578	-0.1055	2.0060	0.343091
344	0.7742	-0.0581	-0.1055	2.0067	0.343022
345	0.7746	-0.0584	-0.1054	2.0073	0.342954
346	0.7750	-0.0587	-0.1053	2.0080	0.342888
347	0.7754	-0.0590	-0.1053	2.0086	0.342823
348	0.7757	-0.0593	-0.1052	2.0092	0.342759
349	0.7761	-0.0596	-0.1052	2.0099	0.342696
350	0.7765	-0.0598	-0.1051	2.0105	0.342634
351	0.7769	-0.0601	-0.1050	2.0111	0.342573
352	0.7772	-0.0604	-0.1050	2.0117	0.342513
353	0.7776	-0.0607	-0.1049	2.0123	0.342455
354	0.7779	-0.0610	-0.1048	2.0129	0.342397
355	0.7783	-0.0613	-0.1048	2.0135	0.342340
356	0.7786	-0.0616	-0.1047	2.0141	0.342284
357	0.7790	-0.0618	-0.1047	2.0146	0.342229
358	0.7794	-0.0621	-0.1046	2.0152	0.342175
359	0.7797	-0.0624	-0.1045	2.0158	0.342122
360	0.7800	-0.0627	-0.1045	2.0164	0.342070
361	0.7804	-0.0630	-0.1044	2.0169	0.342019
362	0.7807	-0.0632	-0.1043	2.0175	0.341968
363	0.7811	-0.0635	-0.1043	2.0180	0.341918
364	0.7814	-0.0638	-0.1042	2.0185	0.341870
365	0.7817	-0.0641	-0.1042	2.0191	0.341822
366	0.7821	-0.0643	-0.1041	2.0196	0.341775
367	0.7824	-0.0646	-0.1040	2.0201	0.341728
368	0.7827	-0.0649	-0.1040	2.0206	0.341683
369	0.7830	-0.0651	-0.1039	2.0212	0.341638
370	0.7834	-0.0654	-0.1038	2.0217	0.341594
371	0.7837	-0.0656	-0.1038	2.0222	0.341550
372	0.7840	-0.0659	-0.1037	2.0227	0.341508
373	0.7843	-0.0662	-0.1037	2.0232	0.341466
374	0.7846	-0.0664	-0.1036	2.0236	0.341425
375	0.7849	-0.0667	-0.1035	2.0241	0.341384
376	0.7853	-0.0669	-0.1035	2.0246	0.341344
377	0.7856	-0.0672	-0.1034	2.0251	0.341305
378	0.7859	-0.0674	-0.1033	2.0256	0.341266
379	0.7862	-0.0677	-0.1033	2.0260	0.341229
380	0.7865	-0.0680	-0.1032	2.0265	0.341191
381	0.7868	-0.0682	-0.1032	2.0269	0.341155
382	0.7871	-0.0684	-0.1031	2.0274	0.341119
383	0.7874	-0.0687	-0.1030	2.0278	0.341083
384	0.7877	-0.0689	-0.1030	2.0283	0.341048
385	0.7879	-0.0692	-0.1029	2.0287	0.341014
386	0.7882	-0.0694	-0.1029	2.0291	0.340980
387	0.7885	-0.0697	-0.1028	2.0296	0.340947
388	0.7888	-0.0699	-0.1027	2.0300	0.340914
389	0.7891	-0.0702	-0.1027	2.0304	0.340882
390	0.7894	-0.0704	-0.1026	2.0308	0.340850
391	0.7897	-0.0706	-0.1026	2.0312	0.340819

392	0.7899	-0.0709	-0.1025	2.0316	0.340789
393	0.7902	-0.0711	-0.1024	2.0320	0.340759
394	0.7905	-0.0713	-0.1024	2.0324	0.340729
395	0.7908	-0.0716	-0.1023	2.0328	0.340700
396	0.7910	-0.0718	-0.1023	2.0332	0.340671
397	0.7913	-0.0720	-0.1022	2.0336	0.340643
398	0.7916	-0.0722	-0.1021	2.0340	0.340615
399	0.7918	-0.0725	-0.1021	2.0344	0.340588
400	0.7921	-0.0727	-0.1020	2.0348	0.340561
401	0.7924	-0.0729	-0.1020	2.0351	0.340535
402	0.7926	-0.0731	-0.1019	2.0355	0.340509
403	0.7929	-0.0734	-0.1018	2.0359	0.340483
404	0.7931	-0.0736	-0.1018	2.0362	0.340458
405	0.7934	-0.0738	-0.1017	2.0366	0.340433
406	0.7936	-0.0740	-0.1017	2.0369	0.340409
407	0.7939	-0.0742	-0.1016	2.0373	0.340385
408	0.7941	-0.0745	-0.1016	2.0376	0.340361
409	0.7944	-0.0747	-0.1015	2.0380	0.340338
410	0.7946	-0.0749	-0.1014	2.0383	0.340315
411	0.7949	-0.0751	-0.1014	2.0386	0.340293
412	0.7951	-0.0753	-0.1013	2.0390	0.340271
413	0.7954	-0.0755	-0.1013	2.0393	0.340249
414	0.7956	-0.0757	-0.1012	2.0396	0.340228
415	0.7958	-0.0759	-0.1011	2.0400	0.340207
416	0.7961	-0.0762	-0.1011	2.0403	0.340186
417	0.7963	-0.0764	-0.1010	2.0406	0.340165
418	0.7966	-0.0766	-0.1010	2.0409	0.340145
419	0.7968	-0.0768	-0.1009	2.0412	0.340126
420	0.7970	-0.0770	-0.1009	2.0415	0.340106
421	0.7972	-0.0772	-0.1008	2.0418	0.340087
422	0.7975	-0.0774	-0.1008	2.0421	0.340068
423	0.7977	-0.0776	-0.1007	2.0424	0.340050
424	0.7979	-0.0778	-0.1006	2.0427	0.340031
425	0.7981	-0.0780	-0.1006	2.0430	0.340013
426	0.7984	-0.0782	-0.1005	2.0433	0.339996
427	0.7986	-0.0784	-0.1005	2.0436	0.339978
428	0.7988	-0.0786	-0.1004	2.0439	0.339961
429	0.7990	-0.0788	-0.1004	2.0442	0.339944
430	0.7992	-0.0789	-0.1003	2.0444	0.339928
431	0.7995	-0.0791	-0.1003	2.0447	0.339911
432	0.7997	-0.0793	-0.1002	2.0450	0.339895
433	0.7999	-0.0795	-0.1001	2.0453	0.339879
434	0.8001	-0.0797	-0.1001	2.0455	0.339864
435	0.8003	-0.0799	-0.1000	2.0458	0.339848
436	0.8005	-0.0801	-0.1000	2.0460	0.339833
437	0.8007	-0.0803	-0.0999	2.0463	0.339818
438	0.8009	-0.0804	-0.0999	2.0466	0.339804
439	0.8011	-0.0806	-0.0998	2.0468	0.339789
440	0.8013	-0.0808	-0.0998	2.0471	0.339775
441	0.8015	-0.0810	-0.0997	2.0473	0.339761
442	0.8017	-0.0812	-0.0997	2.0476	0.339747
443	0.8019	-0.0814	-0.0996	2.0478	0.339734
444	0.8021	-0.0815	-0.0996	2.0480	0.339720
445	0.8023	-0.0817	-0.0995	2.0483	0.339707
446	0.8025	-0.0819	-0.0994	2.0485	0.339694
447	0.8027	-0.0821	-0.0994	2.0488	0.339681

448	0.8029	-0.0822	-0.0993	2.0490	0.339669
449	0.8031	-0.0824	-0.0993	2.0492	0.339656
450	0.8033	-0.0826	-0.0992	2.0494	0.339644
451	0.8035	-0.0828	-0.0992	2.0497	0.339632
452	0.8037	-0.0829	-0.0991	2.0499	0.339620
453	0.8039	-0.0831	-0.0991	2.0501	0.339609
454	0.8041	-0.0833	-0.0990	2.0503	0.339597
455	0.8042	-0.0834	-0.0990	2.0505	0.339586
456	0.8044	-0.0836	-0.0989	2.0508	0.339575
457	0.8046	-0.0838	-0.0989	2.0510	0.339564
458	0.8048	-0.0839	-0.0988	2.0512	0.339553
459	0.8050	-0.0841	-0.0988	2.0514	0.339543
460	0.8051	-0.0843	-0.0987	2.0516	0.339532
461	0.8053	-0.0844	-0.0987	2.0518	0.339522
462	0.8055	-0.0846	-0.0986	2.0520	0.339512
463	0.8057	-0.0847	-0.0986	2.0522	0.339502
464	0.8058	-0.0849	-0.0985	2.0524	0.339492
465	0.8060	-0.0851	-0.0985	2.0526	0.339482
466	0.8062	-0.0852	-0.0984	2.0528	0.339472
467	0.8064	-0.0854	-0.0984	2.0530	0.339463
468	0.8065	-0.0855	-0.0983	2.0532	0.339454
469	0.8067	-0.0857	-0.0983	2.0534	0.339445
470	0.8069	-0.0858	-0.0982	2.0535	0.339436
471	0.8070	-0.0860	-0.0982	2.0537	0.339427
472	0.8072	-0.0861	-0.0981	2.0539	0.339418
473	0.8074	-0.0863	-0.0981	2.0541	0.339409
474	0.8075	-0.0865	-0.0981	2.0543	0.339401
475	0.8077	-0.0866	-0.0980	2.0544	0.339393
476	0.8079	-0.0868	-0.0980	2.0546	0.339384
477	0.8080	-0.0869	-0.0979	2.0548	0.339376
478	0.8082	-0.0870	-0.0979	2.0550	0.339368
479	0.8083	-0.0872	-0.0978	2.0551	0.339360
480	0.8085	-0.0873	-0.0978	2.0553	0.339353
481	0.8086	-0.0875	-0.0977	2.0555	0.339345
482	0.8088	-0.0876	-0.0977	2.0556	0.339338
483	0.8090	-0.0878	-0.0976	2.0558	0.339330
484	0.8091	-0.0879	-0.0976	2.0560	0.339323
485	0.8093	-0.0881	-0.0975	2.0561	0.339316
486	0.8094	-0.0882	-0.0975	2.0563	0.339308
487	0.8096	-0.0883	-0.0974	2.0564	0.339302
488	0.8097	-0.0885	-0.0974	2.0566	0.339295
489	0.8099	-0.0886	-0.0974	2.0567	0.339288
490	0.8100	-0.0888	-0.0973	2.0569	0.339281
491	0.8102	-0.0889	-0.0973	2.0570	0.339275
492	0.8103	-0.0890	-0.0972	2.0572	0.339268
493	0.8105	-0.0892	-0.0972	2.0573	0.339262
494	0.8106	-0.0893	-0.0971	2.0575	0.339255
495	0.8107	-0.0894	-0.0971	2.0576	0.339249
496	0.8109	-0.0896	-0.0970	2.0578	0.339243
497	0.8110	-0.0897	-0.0970	2.0579	0.339237
498	0.8112	-0.0898	-0.0970	2.0581	0.339231
499	0.8113	-0.0900	-0.0969	2.0582	0.339225
500	0.8114	-0.0901	-0.0969	2.0583	0.339219
501	0.8116	-0.0902	-0.0968	2.0585	0.339214
502	0.8117	-0.0904	-0.0968	2.0586	0.339208
503	0.8119	-0.0905	-0.0967	2.0587	0.339202

504	0.8120	-0.0906	-0.0967	2.0589	0.339197
505	0.8121	-0.0907	-0.0967	2.0590	0.339192
506	0.8123	-0.0909	-0.0966	2.0591	0.339186
507	0.8124	-0.0910	-0.0966	2.0593	0.339181
508	0.8125	-0.0911	-0.0965	2.0594	0.339176
509	0.8127	-0.0912	-0.0965	2.0595	0.339171
510	0.8128	-0.0914	-0.0965	2.0596	0.339166
511	0.8129	-0.0915	-0.0964	2.0598	0.339161
512	0.8131	-0.0916	-0.0964	2.0599	0.339156
513	0.8132	-0.0917	-0.0963	2.0600	0.339151
514	0.8133	-0.0919	-0.0963	2.0601	0.339146
515	0.8134	-0.0920	-0.0962	2.0602	0.339142
516	0.8136	-0.0921	-0.0962	2.0604	0.339137
517	0.8137	-0.0922	-0.0962	2.0605	0.339133
518	0.8138	-0.0923	-0.0961	2.0606	0.339128
519	0.8139	-0.0925	-0.0961	2.0607	0.339124
520	0.8141	-0.0926	-0.0960	2.0608	0.339119
521	0.8142	-0.0927	-0.0960	2.0609	0.339115
522	0.8143	-0.0928	-0.0960	2.0610	0.339111
523	0.8144	-0.0929	-0.0959	2.0611	0.339107
524	0.8145	-0.0930	-0.0959	2.0613	0.339103
525	0.8147	-0.0931	-0.0959	2.0614	0.339099
526	0.8148	-0.0933	-0.0958	2.0615	0.339095
527	0.8149	-0.0934	-0.0958	2.0616	0.339091
528	0.8150	-0.0935	-0.0957	2.0617	0.339087
529	0.8151	-0.0936	-0.0957	2.0618	0.339083
530	0.8152	-0.0937	-0.0957	2.0619	0.339079
531	0.8154	-0.0938	-0.0956	2.0620	0.339075
532	0.8155	-0.0939	-0.0956	2.0621	0.339072
533	0.8156	-0.0940	-0.0955	2.0622	0.339068
534	0.8157	-0.0941	-0.0955	2.0623	0.339065
535	0.8158	-0.0942	-0.0955	2.0624	0.339061
536	0.8159	-0.0944	-0.0954	2.0625	0.339058
537	0.8160	-0.0945	-0.0954	2.0626	0.339054
538	0.8161	-0.0946	-0.0954	2.0627	0.339051
539	0.8163	-0.0947	-0.0953	2.0627	0.339047
540	0.8164	-0.0948	-0.0953	2.0628	0.339044
541	0.8165	-0.0949	-0.0953	2.0629	0.339041
542	0.8166	-0.0950	-0.0952	2.0630	0.339038
543	0.8167	-0.0951	-0.0952	2.0631	0.339035
544	0.8168	-0.0952	-0.0951	2.0632	0.339031
545	0.8169	-0.0953	-0.0951	2.0633	0.339028
546	0.8170	-0.0954	-0.0951	2.0634	0.339025
547	0.8171	-0.0955	-0.0950	2.0635	0.339022
548	0.8172	-0.0956	-0.0950	2.0635	0.339019
549	0.8173	-0.0957	-0.0950	2.0636	0.339016
550	0.8174	-0.0958	-0.0949	2.0637	0.339014
551	0.8175	-0.0959	-0.0949	2.0638	0.339011
552	0.8176	-0.0960	-0.0949	2.0639	0.339008
553	0.8177	-0.0961	-0.0948	2.0640	0.339005
554	0.8178	-0.0962	-0.0948	2.0640	0.339003
555	0.8179	-0.0963	-0.0948	2.0641	0.339000
556	0.8180	-0.0964	-0.0947	2.0642	0.338997
557	0.8181	-0.0965	-0.0947	2.0643	0.338995
558	0.8182	-0.0966	-0.0947	2.0643	0.338992
559	0.8183	-0.0967	-0.0946	2.0644	0.338990

560	0.8184	-0.0967	-0.0946	2.0645	0.338987
561	0.8185	-0.0968	-0.0946	2.0646	0.338985
562	0.8186	-0.0969	-0.0945	2.0646	0.338982
563	0.8187	-0.0970	-0.0945	2.0647	0.338980
564	0.8188	-0.0971	-0.0945	2.0648	0.338977
565	0.8189	-0.0972	-0.0944	2.0649	0.338975
566	0.8190	-0.0973	-0.0944	2.0649	0.338973
567	0.8191	-0.0974	-0.0944	2.0650	0.338970
568	0.8192	-0.0975	-0.0943	2.0651	0.338968
569	0.8192	-0.0976	-0.0943	2.0651	0.338966
570	0.8193	-0.0977	-0.0943	2.0652	0.338964
571	0.8194	-0.0977	-0.0942	2.0653	0.338962
572	0.8195	-0.0978	-0.0942	2.0653	0.338960
573	0.8196	-0.0979	-0.0942	2.0654	0.338957
574	0.8197	-0.0980	-0.0941	2.0655	0.338955
575	0.8198	-0.0981	-0.0941	2.0655	0.338953
576	0.8199	-0.0982	-0.0941	2.0656	0.338951
577	0.8200	-0.0983	-0.0940	2.0657	0.338949
578	0.8200	-0.0983	-0.0940	2.0657	0.338947
579	0.8201	-0.0984	-0.0940	2.0658	0.338945
580	0.8202	-0.0985	-0.0940	2.0659	0.338944
581	0.8203	-0.0986	-0.0939	2.0659	0.338942
582	0.8204	-0.0987	-0.0939	2.0660	0.338940
583	0.8205	-0.0988	-0.0939	2.0660	0.338938
584	0.8205	-0.0988	-0.0938	2.0661	0.338936
585	0.8206	-0.0989	-0.0938	2.0662	0.338934
586	0.8207	-0.0990	-0.0938	2.0662	0.338933
587	0.8208	-0.0991	-0.0937	2.0663	0.338931
588	0.8209	-0.0992	-0.0937	2.0663	0.338929
589	0.8210	-0.0992	-0.0937	2.0664	0.338927
590	0.8210	-0.0993	-0.0937	2.0664	0.338926
591	0.8211	-0.0994	-0.0936	2.0665	0.338924
592	0.8212	-0.0995	-0.0936	2.0665	0.338922
593	0.8213	-0.0995	-0.0936	2.0666	0.338921
594	0.8214	-0.0996	-0.0935	2.0667	0.338919
595	0.8214	-0.0997	-0.0935	2.0667	0.338918
596	0.8215	-0.0998	-0.0935	2.0668	0.338916
597	0.8216	-0.0998	-0.0935	2.0668	0.338915
598	0.8217	-0.0999	-0.0934	2.0669	0.338913
599	0.8217	-0.1000	-0.0934	2.0669	0.338912
600	0.8218	-0.1001	-0.0934	2.0670	0.338910
601	0.8219	-0.1001	-0.0933	2.0670	0.338909
602	0.8220	-0.1002	-0.0933	2.0671	0.338907
603	0.8220	-0.1003	-0.0933	2.0671	0.338906
604	0.8221	-0.1004	-0.0933	2.0672	0.338904
605	0.8222	-0.1004	-0.0932	2.0672	0.338903
606	0.8223	-0.1005	-0.0932	2.0673	0.338902
607	0.8223	-0.1006	-0.0932	2.0673	0.338900
608	0.8224	-0.1007	-0.0932	2.0673	0.338899
609	0.8225	-0.1007	-0.0931	2.0674	0.338898
610	0.8225	-0.1008	-0.0931	2.0674	0.338896
611	0.8226	-0.1009	-0.0931	2.0675	0.338895
612	0.8227	-0.1009	-0.0931	2.0675	0.338894
613	0.8228	-0.1010	-0.0930	2.0676	0.338893
614	0.8228	-0.1011	-0.0930	2.0676	0.338892
615	0.8229	-0.1011	-0.0930	2.0677	0.338890

616	0.8230	-0.1012	-0.0929	2.0677	0.338889
617	0.8230	-0.1013	-0.0929	2.0677	0.338888
618	0.8231	-0.1013	-0.0929	2.0678	0.338887
619	0.8232	-0.1014	-0.0929	2.0678	0.338886
620	0.8232	-0.1015	-0.0928	2.0679	0.338884
621	0.8233	-0.1015	-0.0928	2.0679	0.338883
622	0.8234	-0.1016	-0.0928	2.0680	0.338882
623	0.8234	-0.1017	-0.0928	2.0680	0.338881
624	0.8235	-0.1017	-0.0927	2.0680	0.338880
625	0.8236	-0.1018	-0.0927	2.0681	0.338879
626	0.8236	-0.1019	-0.0927	2.0681	0.338878
627	0.8237	-0.1019	-0.0927	2.0681	0.338877
628	0.8238	-0.1020	-0.0926	2.0682	0.338876
629	0.8238	-0.1021	-0.0926	2.0682	0.338875
630	0.8239	-0.1021	-0.0926	2.0683	0.338874
631	0.8239	-0.1022	-0.0926	2.0683	0.338873
632	0.8240	-0.1022	-0.0926	2.0683	0.338872
633	0.8241	-0.1023	-0.0925	2.0684	0.338871
634	0.8241	-0.1024	-0.0925	2.0684	0.338870
635	0.8242	-0.1024	-0.0925	2.0684	0.338869
636	0.8243	-0.1025	-0.0925	2.0685	0.338868
637	0.8243	-0.1025	-0.0924	2.0685	0.338867
638	0.8244	-0.1026	-0.0924	2.0685	0.338866
639	0.8244	-0.1027	-0.0924	2.0686	0.338866
640	0.8245	-0.1027	-0.0924	2.0686	0.338865
641	0.8246	-0.1028	-0.0923	2.0686	0.338864
642	0.8246	-0.1028	-0.0923	2.0687	0.338863
643	0.8247	-0.1029	-0.0923	2.0687	0.338862
644	0.8247	-0.1030	-0.0923	2.0687	0.338861
645	0.8248	-0.1030	-0.0923	2.0688	0.338860
646	0.8248	-0.1031	-0.0922	2.0688	0.338860
647	0.8249	-0.1031	-0.0922	2.0688	0.338859
648	0.8250	-0.1032	-0.0922	2.0689	0.338858
649	0.8250	-0.1032	-0.0922	2.0689	0.338857
650	0.8251	-0.1033	-0.0921	2.0689	0.338856
651	0.8251	-0.1033	-0.0921	2.0690	0.338856
652	0.8252	-0.1034	-0.0921	2.0690	0.338855
653	0.8252	-0.1035	-0.0921	2.0690	0.338854
654	0.8253	-0.1035	-0.0921	2.0691	0.338853
655	0.8253	-0.1036	-0.0920	2.0691	0.338853
656	0.8254	-0.1036	-0.0920	2.0691	0.338852
657	0.8255	-0.1037	-0.0920	2.0691	0.338851
658	0.8255	-0.1037	-0.0920	2.0692	0.338851
659	0.8256	-0.1038	-0.0920	2.0692	0.338850
660	0.8256	-0.1038	-0.0919	2.0692	0.338849
661	0.8257	-0.1039	-0.0919	2.0692	0.338849
662	0.8257	-0.1039	-0.0919	2.0693	0.338848
663	0.8258	-0.1040	-0.0919	2.0693	0.338847
664	0.8258	-0.1040	-0.0919	2.0693	0.338847
665	0.8259	-0.1041	-0.0918	2.0694	0.338846
666	0.8259	-0.1041	-0.0918	2.0694	0.338845
667	0.8260	-0.1042	-0.0918	2.0694	0.338845
668	0.8260	-0.1042	-0.0918	2.0694	0.338844
669	0.8261	-0.1043	-0.0918	2.0695	0.338844
670	0.8261	-0.1043	-0.0917	2.0695	0.338843
671	0.8262	-0.1044	-0.0917	2.0695	0.338842

672	0.8262	-0.1044	-0.0917	2.0695	0.338842
673	0.8263	-0.1045	-0.0917	2.0696	0.338841
674	0.8263	-0.1045	-0.0917	2.0696	0.338841
675	0.8264	-0.1046	-0.0916	2.0696	0.338840
676	0.8264	-0.1046	-0.0916	2.0696	0.338839
677	0.8265	-0.1047	-0.0916	2.0696	0.338839
678	0.8265	-0.1047	-0.0916	2.0697	0.338838
679	0.8266	-0.1048	-0.0916	2.0697	0.338838
680	0.8266	-0.1048	-0.0915	2.0697	0.338837
681	0.8267	-0.1049	-0.0915	2.0697	0.338837
682	0.8267	-0.1049	-0.0915	2.0698	0.338836
683	0.8267	-0.1050	-0.0915	2.0698	0.338836
684	0.8268	-0.1050	-0.0915	2.0698	0.338835
685	0.8268	-0.1051	-0.0915	2.0698	0.338835
686	0.8269	-0.1051	-0.0914	2.0698	0.338834
687	0.8269	-0.1051	-0.0914	2.0699	0.338834
688	0.8270	-0.1052	-0.0914	2.0699	0.338833
689	0.8270	-0.1052	-0.0914	2.0699	0.338833
690	0.8271	-0.1053	-0.0914	2.0699	0.338832
691	0.8271	-0.1053	-0.0913	2.0700	0.338832
692	0.8271	-0.1054	-0.0913	2.0700	0.338831
693	0.8272	-0.1054	-0.0913	2.0700	0.338831
694	0.8272	-0.1055	-0.0913	2.0700	0.338831
695	0.8273	-0.1055	-0.0913	2.0700	0.338830
696	0.8273	-0.1055	-0.0913	2.0700	0.338830
697	0.8274	-0.1056	-0.0912	2.0701	0.338829
698	0.8274	-0.1056	-0.0912	2.0701	0.338829
699	0.8274	-0.1057	-0.0912	2.0701	0.338828
700	0.8275	-0.1057	-0.0912	2.0701	0.338828
701	0.8275	-0.1058	-0.0912	2.0701	0.338828
702	0.8276	-0.1058	-0.0912	2.0702	0.338827
703	0.8276	-0.1058	-0.0911	2.0702	0.338827
704	0.8277	-0.1059	-0.0911	2.0702	0.338826
705	0.8277	-0.1059	-0.0911	2.0702	0.338826
706	0.8277	-0.1060	-0.0911	2.0702	0.338826
707	0.8278	-0.1060	-0.0911	2.0702	0.338825
708	0.8278	-0.1060	-0.0911	2.0703	0.338825
709	0.8279	-0.1061	-0.0910	2.0703	0.338824
710	0.8279	-0.1061	-0.0910	2.0703	0.338824
711	0.8279	-0.1062	-0.0910	2.0703	0.338824
712	0.8280	-0.1062	-0.0910	2.0703	0.338823
713	0.8280	-0.1062	-0.0910	2.0703	0.338823
714	0.8280	-0.1063	-0.0910	2.0704	0.338823
715	0.8281	-0.1063	-0.0909	2.0704	0.338822
716	0.8281	-0.1063	-0.0909	2.0704	0.338822
717	0.8282	-0.1064	-0.0909	2.0704	0.338822
718	0.8282	-0.1064	-0.0909	2.0704	0.338821
719	0.8282	-0.1065	-0.0909	2.0704	0.338821
720	0.8283	-0.1065	-0.0909	2.0705	0.338821
721	0.8283	-0.1065	-0.0909	2.0705	0.338820
722	0.8283	-0.1066	-0.0908	2.0705	0.338820
723	0.8284	-0.1066	-0.0908	2.0705	0.338820
724	0.8284	-0.1066	-0.0908	2.0705	0.338819
725	0.8285	-0.1067	-0.0908	2.0705	0.338819
726	0.8285	-0.1067	-0.0908	2.0705	0.338819
727	0.8285	-0.1068	-0.0908	2.0706	0.338818

728	0.8286	-0.1068	-0.0908	2.0706	0.338818
729	0.8286	-0.1068	-0.0907	2.0706	0.338818
730	0.8286	-0.1069	-0.0907	2.0706	0.338818
731	0.8287	-0.1069	-0.0907	2.0706	0.338817
732	0.8287	-0.1069	-0.0907	2.0706	0.338817
733	0.8287	-0.1070	-0.0907	2.0706	0.338817
734	0.8288	-0.1070	-0.0907	2.0707	0.338816
735	0.8288	-0.1070	-0.0907	2.0707	0.338816
736	0.8288	-0.1071	-0.0906	2.0707	0.338816
737	0.8289	-0.1071	-0.0906	2.0707	0.338816
738	0.8289	-0.1071	-0.0906	2.0707	0.338815
739	0.8289	-0.1072	-0.0906	2.0707	0.338815
740	0.8290	-0.1072	-0.0906	2.0707	0.338815
741	0.8290	-0.1072	-0.0906	2.0707	0.338815
742	0.8290	-0.1073	-0.0906	2.0708	0.338814
743	0.8291	-0.1073	-0.0905	2.0708	0.338814
744	0.8291	-0.1073	-0.0905	2.0708	0.338814
745	0.8291	-0.1074	-0.0905	2.0708	0.338814
746	0.8292	-0.1074	-0.0905	2.0708	0.338813
747	0.8292	-0.1074	-0.0905	2.0708	0.338813
748	0.8292	-0.1075	-0.0905	2.0708	0.338813
749	0.8293	-0.1075	-0.0905	2.0708	0.338813
750	0.8293	-0.1075	-0.0905	2.0708	0.338813
751	0.8293	-0.1076	-0.0904	2.0709	0.338812
752	0.8293	-0.1076	-0.0904	2.0709	0.338812
753	0.8294	-0.1076	-0.0904	2.0709	0.338812
754	0.8294	-0.1076	-0.0904	2.0709	0.338812
755	0.8294	-0.1077	-0.0904	2.0709	0.338811
756	0.8295	-0.1077	-0.0904	2.0709	0.338811
757	0.8295	-0.1077	-0.0904	2.0709	0.338811
758	0.8295	-0.1078	-0.0903	2.0709	0.338811
759	0.8296	-0.1078	-0.0903	2.0709	0.338811
760	0.8296	-0.1078	-0.0903	2.0709	0.338810
761	0.8296	-0.1079	-0.0903	2.0710	0.338810
762	0.8296	-0.1079	-0.0903	2.0710	0.338810
763	0.8297	-0.1079	-0.0903	2.0710	0.338810
764	0.8297	-0.1079	-0.0903	2.0710	0.338810
765	0.8297	-0.1080	-0.0903	2.0710	0.338809
766	0.8298	-0.1080	-0.0903	2.0710	0.338809
767	0.8298	-0.1080	-0.0902	2.0710	0.338809
768	0.8298	-0.1081	-0.0902	2.0710	0.338809
769	0.8298	-0.1081	-0.0902	2.0710	0.338809
770	0.8299	-0.1081	-0.0902	2.0710	0.338809
771	0.8299	-0.1081	-0.0902	2.0711	0.338808
772	0.8299	-0.1082	-0.0902	2.0711	0.338808
773	0.8300	-0.1082	-0.0902	2.0711	0.338808
774	0.8300	-0.1082	-0.0902	2.0711	0.338808
775	0.8300	-0.1082	-0.0901	2.0711	0.338808
776	0.8300	-0.1083	-0.0901	2.0711	0.338808
777	0.8301	-0.1083	-0.0901	2.0711	0.338807
778	0.8301	-0.1083	-0.0901	2.0711	0.338807
779	0.8301	-0.1084	-0.0901	2.0711	0.338807
780	0.8301	-0.1084	-0.0901	2.0711	0.338807
781	0.8302	-0.1084	-0.0901	2.0711	0.338807
782	0.8302	-0.1084	-0.0901	2.0711	0.338807
783	0.8302	-0.1085	-0.0901	2.0712	0.338806

784	0.8302	-0.1085	-0.0901	2.0712	0.338806
785	0.8303	-0.1085	-0.0900	2.0712	0.338806
786	0.8303	-0.1085	-0.0900	2.0712	0.338806
787	0.8303	-0.1086	-0.0900	2.0712	0.338806
788	0.8303	-0.1086	-0.0900	2.0712	0.338806
789	0.8304	-0.1086	-0.0900	2.0712	0.338806
790	0.8304	-0.1086	-0.0900	2.0712	0.338805
791	0.8304	-0.1087	-0.0900	2.0712	0.338805
792	0.8304	-0.1087	-0.0900	2.0712	0.338805
793	0.8305	-0.1087	-0.0900	2.0712	0.338805
794	0.8305	-0.1087	-0.0899	2.0712	0.338805
795	0.8305	-0.1088	-0.0899	2.0712	0.338805
796	0.8305	-0.1088	-0.0899	2.0713	0.338805
797	0.8306	-0.1088	-0.0899	2.0713	0.338804
798	0.8306	-0.1088	-0.0899	2.0713	0.338804
799	0.8306	-0.1089	-0.0899	2.0713	0.338804
800	0.8306	-0.1089	-0.0899	2.0713	0.338804
801	0.8307	-0.1089	-0.0899	2.0713	0.338804
802	0.8307	-0.1089	-0.0899	2.0713	0.338804
803	0.8307	-0.1089	-0.0899	2.0713	0.338804
804	0.8307	-0.1090	-0.0898	2.0713	0.338804
805	0.8307	-0.1090	-0.0898	2.0713	0.338803
806	0.8308	-0.1090	-0.0898	2.0713	0.338803
807	0.8308	-0.1090	-0.0898	2.0713	0.338803
808	0.8308	-0.1091	-0.0898	2.0713	0.338803
809	0.8308	-0.1091	-0.0898	2.0713	0.338803
810	0.8309	-0.1091	-0.0898	2.0713	0.338803
811	0.8309	-0.1091	-0.0898	2.0713	0.338803
812	0.8309	-0.1091	-0.0898	2.0714	0.338803
813	0.8309	-0.1092	-0.0898	2.0714	0.338803
814	0.8309	-0.1092	-0.0898	2.0714	0.338802
815	0.8310	-0.1092	-0.0897	2.0714	0.338802
816	0.8310	-0.1092	-0.0897	2.0714	0.338802
817	0.8310	-0.1093	-0.0897	2.0714	0.338802
818	0.8310	-0.1093	-0.0897	2.0714	0.338802
819	0.8310	-0.1093	-0.0897	2.0714	0.338802
820	0.8311	-0.1093	-0.0897	2.0714	0.338802
821	0.8311	-0.1093	-0.0897	2.0714	0.338802
822	0.8311	-0.1094	-0.0897	2.0714	0.338802
823	0.8311	-0.1094	-0.0897	2.0714	0.338802
824	0.8311	-0.1094	-0.0897	2.0714	0.338801
825	0.8312	-0.1094	-0.0897	2.0714	0.338801
826	0.8312	-0.1094	-0.0896	2.0714	0.338801
827	0.8312	-0.1095	-0.0896	2.0714	0.338801
828	0.8312	-0.1095	-0.0896	2.0714	0.338801
829	0.8312	-0.1095	-0.0896	2.0714	0.338801
830	0.8313	-0.1095	-0.0896	2.0715	0.338801
831	0.8313	-0.1095	-0.0896	2.0715	0.338801
832	0.8313	-0.1096	-0.0896	2.0715	0.338801
833	0.8313	-0.1096	-0.0896	2.0715	0.338801
834	0.8313	-0.1096	-0.0896	2.0715	0.338801
835	0.8314	-0.1096	-0.0896	2.0715	0.338801
836	0.8314	-0.1096	-0.0896	2.0715	0.338800
837	0.8314	-0.1097	-0.0896	2.0715	0.338800
838	0.8314	-0.1097	-0.0895	2.0715	0.338800
839	0.8314	-0.1097	-0.0895	2.0715	0.338800

840	0.8315	-0.1097	-0.0895	2.0715	0.338800
841	0.8315	-0.1097	-0.0895	2.0715	0.338800
842	0.8315	-0.1097	-0.0895	2.0715	0.338800
843	0.8315	-0.1098	-0.0895	2.0715	0.338800
844	0.8315	-0.1098	-0.0895	2.0715	0.338800
845	0.8315	-0.1098	-0.0895	2.0715	0.338800
846	0.8316	-0.1098	-0.0895	2.0715	0.338800
847	0.8316	-0.1098	-0.0895	2.0715	0.338800
848	0.8316	-0.1099	-0.0895	2.0715	0.338800
849	0.8316	-0.1099	-0.0895	2.0715	0.338799
850	0.8316	-0.1099	-0.0895	2.0715	0.338799
851	0.8316	-0.1099	-0.0894	2.0715	0.338799
852	0.8317	-0.1099	-0.0894	2.0716	0.338799
853	0.8317	-0.1099	-0.0894	2.0716	0.338799
854	0.8317	-0.1100	-0.0894	2.0716	0.338799
855	0.8317	-0.1100	-0.0894	2.0716	0.338799
856	0.8317	-0.1100	-0.0894	2.0716	0.338799
857	0.8317	-0.1100	-0.0894	2.0716	0.338799
858	0.8318	-0.1100	-0.0894	2.0716	0.338799
859	0.8318	-0.1100	-0.0894	2.0716	0.338799
860	0.8318	-0.1101	-0.0894	2.0716	0.338799
861	0.8318	-0.1101	-0.0894	2.0716	0.338799
862	0.8318	-0.1101	-0.0894	2.0716	0.338799
863	0.8318	-0.1101	-0.0894	2.0716	0.338799
864	0.8319	-0.1101	-0.0894	2.0716	0.338799
865	0.8319	-0.1101	-0.0893	2.0716	0.338798
866	0.8319	-0.1102	-0.0893	2.0716	0.338798
867	0.8319	-0.1102	-0.0893	2.0716	0.338798
868	0.8319	-0.1102	-0.0893	2.0716	0.338798
869	0.8319	-0.1102	-0.0893	2.0716	0.338798
870	0.8320	-0.1102	-0.0893	2.0716	0.338798
871	0.8320	-0.1102	-0.0893	2.0716	0.338798
872	0.8320	-0.1103	-0.0893	2.0716	0.338798
873	0.8320	-0.1103	-0.0893	2.0716	0.338798
874	0.8320	-0.1103	-0.0893	2.0716	0.338798
875	0.8320	-0.1103	-0.0893	2.0716	0.338798
876	0.8320	-0.1103	-0.0893	2.0716	0.338798
877	0.8321	-0.1103	-0.0893	2.0716	0.338798
878	0.8321	-0.1103	-0.0893	2.0716	0.338798
879	0.8321	-0.1104	-0.0893	2.0716	0.338798
880	0.8321	-0.1104	-0.0892	2.0716	0.338798
881	0.8321	-0.1104	-0.0892	2.0717	0.338798
882	0.8321	-0.1104	-0.0892	2.0717	0.338798
883	0.8321	-0.1104	-0.0892	2.0717	0.338798
884	0.8322	-0.1104	-0.0892	2.0717	0.338798
885	0.8322	-0.1104	-0.0892	2.0717	0.338797
886	0.8322	-0.1105	-0.0892	2.0717	0.338797
887	0.8322	-0.1105	-0.0892	2.0717	0.338797
888	0.8322	-0.1105	-0.0892	2.0717	0.338797
889	0.8322	-0.1105	-0.0892	2.0717	0.338797
890	0.8322	-0.1105	-0.0892	2.0717	0.338797
891	0.8323	-0.1105	-0.0892	2.0717	0.338797
892	0.8323	-0.1105	-0.0892	2.0717	0.338797
893	0.8323	-0.1106	-0.0892	2.0717	0.338797
894	0.8323	-0.1106	-0.0892	2.0717	0.338797
895	0.8323	-0.1106	-0.0892	2.0717	0.338797

896	0.8323	-0.1106	-0.0891	2.0717	0.338797
897	0.8323	-0.1106	-0.0891	2.0717	0.338797
898	0.8324	-0.1106	-0.0891	2.0717	0.338797
899	0.8324	-0.1106	-0.0891	2.0717	0.338797
900	0.8324	-0.1107	-0.0891	2.0717	0.338797
901	0.8324	-0.1107	-0.0891	2.0717	0.338797
902	0.8324	-0.1107	-0.0891	2.0717	0.338797
903	0.8324	-0.1107	-0.0891	2.0717	0.338797
904	0.8324	-0.1107	-0.0891	2.0717	0.338797
905	0.8324	-0.1107	-0.0891	2.0717	0.338797
906	0.8325	-0.1107	-0.0891	2.0717	0.338797
907	0.8325	-0.1107	-0.0891	2.0717	0.338797
908	0.8325	-0.1108	-0.0891	2.0717	0.338797
909	0.8325	-0.1108	-0.0891	2.0717	0.338797
910	0.8325	-0.1108	-0.0891	2.0717	0.338796
911	0.8325	-0.1108	-0.0891	2.0717	0.338796
912	0.8325	-0.1108	-0.0891	2.0717	0.338796
913	0.8325	-0.1108	-0.0891	2.0717	0.338796
914	0.8326	-0.1108	-0.0890	2.0717	0.338796
915	0.8326	-0.1108	-0.0890	2.0717	0.338796
916	0.8326	-0.1109	-0.0890	2.0717	0.338796
917	0.8326	-0.1109	-0.0890	2.0717	0.338796
918	0.8326	-0.1109	-0.0890	2.0717	0.338796
919	0.8326	-0.1109	-0.0890	2.0717	0.338796
920	0.8326	-0.1109	-0.0890	2.0717	0.338796
921	0.8326	-0.1109	-0.0890	2.0717	0.338796
922	0.8326	-0.1109	-0.0890	2.0718	0.338796
923	0.8327	-0.1109	-0.0890	2.0718	0.338796
924	0.8327	-0.1109	-0.0890	2.0718	0.338796
925	0.8327	-0.1110	-0.0890	2.0718	0.338796
926	0.8327	-0.1110	-0.0890	2.0718	0.338796
927	0.8327	-0.1110	-0.0890	2.0718	0.338796
928	0.8327	-0.1110	-0.0890	2.0718	0.338796
929	0.8327	-0.1110	-0.0890	2.0718	0.338796
930	0.8327	-0.1110	-0.0890	2.0718	0.338796
931	0.8327	-0.1110	-0.0890	2.0718	0.338796
932	0.8328	-0.1110	-0.0890	2.0718	0.338796
933	0.8328	-0.1110	-0.0890	2.0718	0.338796
934	0.8328	-0.1111	-0.0890	2.0718	0.338796
935	0.8328	-0.1111	-0.0889	2.0718	0.338796
936	0.8328	-0.1111	-0.0889	2.0718	0.338796
937	0.8328	-0.1111	-0.0889	2.0718	0.338796
938	0.8328	-0.1111	-0.0889	2.0718	0.338796
939	0.8328	-0.1111	-0.0889	2.0718	0.338796
940	0.8328	-0.1111	-0.0889	2.0718	0.338796
941	0.8328	-0.1111	-0.0889	2.0718	0.338796
942	0.8329	-0.1111	-0.0889	2.0718	0.338796
943	0.8329	-0.1112	-0.0889	2.0718	0.338796
944	0.8329	-0.1112	-0.0889	2.0718	0.338796
945	0.8329	-0.1112	-0.0889	2.0718	0.338796
946	0.8329	-0.1112	-0.0889	2.0718	0.338795
947	0.8329	-0.1112	-0.0889	2.0718	0.338795
948	0.8329	-0.1112	-0.0889	2.0718	0.338795
949	0.8329	-0.1112	-0.0889	2.0718	0.338795
950	0.8329	-0.1112	-0.0889	2.0718	0.338795
951	0.8329	-0.1112	-0.0889	2.0718	0.338795

952	0.8330	-0.1112	-0.0889	2.0718	0.338795
953	0.8330	-0.1113	-0.0889	2.0718	0.338795
954	0.8330	-0.1113	-0.0889	2.0718	0.338795
955	0.8330	-0.1113	-0.0889	2.0718	0.338795
956	0.8330	-0.1113	-0.0889	2.0718	0.338795
957	0.8330	-0.1113	-0.0888	2.0718	0.338795
958	0.8330	-0.1113	-0.0888	2.0718	0.338795
959	0.8330	-0.1113	-0.0888	2.0718	0.338795
960	0.8330	-0.1113	-0.0888	2.0718	0.338795
961	0.8330	-0.1113	-0.0888	2.0718	0.338795
962	0.8330	-0.1113	-0.0888	2.0718	0.338795
963	0.8331	-0.1113	-0.0888	2.0718	0.338795
964	0.8331	-0.1114	-0.0888	2.0718	0.338795
965	0.8331	-0.1114	-0.0888	2.0718	0.338795
966	0.8331	-0.1114	-0.0888	2.0718	0.338795
967	0.8331	-0.1114	-0.0888	2.0718	0.338795
968	0.8331	-0.1114	-0.0888	2.0718	0.338795
969	0.8331	-0.1114	-0.0888	2.0718	0.338795
970	0.8331	-0.1114	-0.0888	2.0718	0.338795
971	0.8331	-0.1114	-0.0888	2.0718	0.338795
972	0.8331	-0.1114	-0.0888	2.0718	0.338795
973	0.8331	-0.1114	-0.0888	2.0718	0.338795
974	0.8332	-0.1114	-0.0888	2.0718	0.338795
975	0.8332	-0.1115	-0.0888	2.0718	0.338795
976	0.8332	-0.1115	-0.0888	2.0718	0.338795
977	0.8332	-0.1115	-0.0888	2.0718	0.338795
978	0.8332	-0.1115	-0.0888	2.0718	0.338795
979	0.8332	-0.1115	-0.0888	2.0718	0.338795
980	0.8332	-0.1115	-0.0888	2.0718	0.338795
981	0.8332	-0.1115	-0.0888	2.0718	0.338795
982	0.8332	-0.1115	-0.0888	2.0718	0.338795
983	0.8332	-0.1115	-0.0887	2.0718	0.338795
984	0.8332	-0.1115	-0.0887	2.0718	0.338795
985	0.8332	-0.1115	-0.0887	2.0718	0.338795
986	0.8333	-0.1115	-0.0887	2.0718	0.338795
987	0.8333	-0.1116	-0.0887	2.0718	0.338795
988	0.8333	-0.1116	-0.0887	2.0718	0.338795
989	0.8333	-0.1116	-0.0887	2.0718	0.338795
990	0.8333	-0.1116	-0.0887	2.0718	0.338795
991	0.8333	-0.1116	-0.0887	2.0718	0.338795
992	0.8333	-0.1116	-0.0887	2.0718	0.338795
993	0.8333	-0.1116	-0.0887	2.0719	0.338795
994	0.8333	-0.1116	-0.0887	2.0719	0.338795
995	0.8333	-0.1116	-0.0887	2.0719	0.338795
996	0.8333	-0.1116	-0.0887	2.0719	0.338795
997	0.8333	-0.1116	-0.0887	2.0719	0.338795
998	0.8333	-0.1116	-0.0887	2.0719	0.338795
999	0.8333	-0.1116	-0.0887	2.0719	0.338795
1000	0.8334	-0.1117	-0.0887	2.0719	0.338795

In [15]:
```
print("Final weights:\n", w_final)
print("Final bias:\n", b_final)
```

```
Final weights:
 [[ 0.83335553]
 [-0.11165152]
 [-0.08869069]]
Final bias:
 2.0718574888450343
```

Mini Batch GD :

In [16]:
```python
def mini_batch_sgd_verbose(X, y, w_init, b_init, eta=0.01, max_iter=1000, batch_fra
    N, d = X.shape
    batch_size = max(1, int(N * batch_frac))
    w = w_init.copy()
    b = b_init
    J_history = []

    print(f"\nMini-Batch {int(batch_frac*100)}% Convergence")
    print(f"{'Iteration':>10} {'w1':>10} {'w2':>10} {'w3':>10} {'b':>10} {'J(w,b)':

    for iter_num in range(max_iter):
        # Shuffle
        indices = np.arange(N)
        np.random.shuffle(indices)
        X_shuffled = X[indices]
        y_shuffled = y[indices]

        for start in range(0, N, batch_size):
            end = start + batch_size
            X_batch = X_shuffled[start:end]
            y_batch = y_shuffled[start:end]

            y_hat = np.dot(X_batch, w) + b
            e = y_hat - y_batch

            dw = (1/batch_size) * np.dot(X_batch.T, e)
            db = (1/batch_size) * np.sum(e)

            w -= eta * dw
            b -= eta * db

        # Full dataset objective
        y_hat_full = np.dot(X, w) + b
        e_full = y_hat_full - y
        J = (1/(2*N)) * np.sum(e_full**2)
        J_history.append(J)

        # Print iteration-wise values
        print(f"{iter_num+1:>10} {w[0,0]:>10.4f} {w[1,0]:>10.4f} {w[2,0]:>10.4f} {b

        if np.linalg.norm(dw) < epsilon and abs(db) < epsilon:
            print(f"Converged at iteration {iter_num+1}")
            break

    return w, b, J_history
```

```
# Run mini-batch SGD for 10%, 20%, 25%
batch_fractions = [0.1, 0.2, 0.25]
results = {}

for frac in batch_fractions:
    w_mini, b_mini, J_hist_mini = mini_batch_sgd_verbose(X_train, y_train, w0, b0,
                                                       eta, max_iter, batch_frac=
    results[frac] = (w_mini, b_mini, J_hist_mini)
```

Mini-Batch 10% Convergence

Iteration	w1	w2	w3	b	J(w,b)
1	0.0760	0.0173	-0.0156	0.1981	2.361016
2	0.1441	0.0304	-0.0294	0.3773	1.991563
3	0.2052	0.0401	-0.0416	0.5394	1.690562
4	0.2600	0.0469	-0.0522	0.6860	1.445201
5	0.3093	0.0513	-0.0615	0.8185	1.245081
6	0.3537	0.0536	-0.0696	0.9384	1.081651
7	0.3937	0.0543	-0.0766	1.0468	0.948182
8	0.4299	0.0535	-0.0827	1.1448	0.839076
9	0.4626	0.0517	-0.0880	1.2335	0.749847
10	0.4922	0.0489	-0.0924	1.3136	0.676834
11	0.5190	0.0455	-0.0962	1.3861	0.617032
12	0.5435	0.0414	-0.0995	1.4517	0.568007
13	0.5657	0.0370	-0.1021	1.5110	0.527802
14	0.5859	0.0323	-0.1044	1.5646	0.494799
15	0.6044	0.0273	-0.1061	1.6131	0.467680
16	0.6213	0.0221	-0.1076	1.6570	0.445394
17	0.6368	0.0170	-0.1087	1.6967	0.427049
18	0.6510	0.0117	-0.1096	1.7326	0.411939
19	0.6639	0.0065	-0.1102	1.7650	0.399509
20	0.6758	0.0013	-0.1106	1.7944	0.389246
21	0.6868	-0.0038	-0.1109	1.8209	0.380768
22	0.6969	-0.0087	-0.1109	1.8449	0.373768
23	0.7062	-0.0136	-0.1109	1.8666	0.367980
24	0.7148	-0.0183	-0.1107	1.8863	0.363184
25	0.7227	-0.0228	-0.1104	1.9040	0.359209
26	0.7301	-0.0273	-0.1101	1.9201	0.355908
27	0.7369	-0.0315	-0.1096	1.9346	0.353167
28	0.7432	-0.0356	-0.1092	1.9477	0.350877
29	0.7491	-0.0396	-0.1087	1.9596	0.348971
30	0.7545	-0.0434	-0.1082	1.9703	0.347381
31	0.7596	-0.0470	-0.1076	1.9801	0.346054
32	0.7643	-0.0504	-0.1069	1.9888	0.344944
33	0.7687	-0.0536	-0.1063	1.9968	0.344015
34	0.7728	-0.0567	-0.1057	2.0040	0.343231
35	0.7766	-0.0597	-0.1051	2.0105	0.342574
36	0.7801	-0.0625	-0.1045	2.0163	0.342020
37	0.7834	-0.0653	-0.1039	2.0216	0.341552
38	0.7866	-0.0678	-0.1032	2.0265	0.341156
39	0.7895	-0.0702	-0.1026	2.0308	0.340820
40	0.7921	-0.0726	-0.1020	2.0348	0.340537
41	0.7946	-0.0748	-0.1014	2.0383	0.340293
42	0.7970	-0.0769	-0.1008	2.0416	0.340088
43	0.7993	-0.0788	-0.1003	2.0445	0.339912
44	0.8014	-0.0807	-0.0997	2.0471	0.339761
45	0.8033	-0.0824	-0.0992	2.0495	0.339634
46	0.8051	-0.0841	-0.0987	2.0516	0.339524
47	0.8068	-0.0857	-0.0982	2.0535	0.339429
48	0.8085	-0.0872	-0.0977	2.0553	0.339348
49	0.8100	-0.0886	-0.0973	2.0569	0.339277
50	0.8113	-0.0901	-0.0969	2.0583	0.339216
51	0.8127	-0.0914	-0.0964	2.0596	0.339163
52	0.8140	-0.0926	-0.0961	2.0608	0.339117
53	0.8152	-0.0937	-0.0957	2.0619	0.339077
54	0.8163	-0.0947	-0.0953	2.0628	0.339042

55	0.8174	-0.0958	-0.0950	2.0637	0.339011
56	0.8183	-0.0968	-0.0946	2.0645	0.338985
57	0.8193	-0.0976	-0.0943	2.0652	0.338962
58	0.8202	-0.0985	-0.0940	2.0659	0.338942
59	0.8209	-0.0994	-0.0937	2.0664	0.338924
60	0.8217	-0.1001	-0.0934	2.0669	0.338909
61	0.8225	-0.1008	-0.0931	2.0674	0.338896
62	0.8231	-0.1015	-0.0929	2.0679	0.338884
63	0.8238	-0.1021	-0.0926	2.0683	0.338874
64	0.8244	-0.1027	-0.0924	2.0686	0.338865
65	0.8250	-0.1033	-0.0922	2.0689	0.338856
66	0.8256	-0.1038	-0.0919	2.0692	0.338849
67	0.8261	-0.1043	-0.0917	2.0695	0.338843
68	0.8265	-0.1048	-0.0915	2.0697	0.338837
69	0.8269	-0.1054	-0.0914	2.0699	0.338832
70	0.8274	-0.1057	-0.0912	2.0701	0.338828
71	0.8278	-0.1061	-0.0911	2.0703	0.338824
72	0.8282	-0.1065	-0.0909	2.0704	0.338821
73	0.8286	-0.1068	-0.0908	2.0705	0.338818
74	0.8289	-0.1071	-0.0906	2.0707	0.338815
75	0.8293	-0.1074	-0.0905	2.0708	0.338813
76	0.8296	-0.1077	-0.0903	2.0709	0.338811
77	0.8299	-0.1080	-0.0902	2.0710	0.338809
78	0.8301	-0.1083	-0.0901	2.0711	0.338807
79	0.8304	-0.1086	-0.0900	2.0712	0.338806
80	0.8306	-0.1088	-0.0899	2.0712	0.338804
81	0.8308	-0.1091	-0.0898	2.0713	0.338803
82	0.8310	-0.1093	-0.0897	2.0713	0.338802
83	0.8312	-0.1095	-0.0896	2.0714	0.338801
84	0.8314	-0.1097	-0.0895	2.0715	0.338800
85	0.8316	-0.1099	-0.0894	2.0715	0.338799
86	0.8317	-0.1101	-0.0894	2.0716	0.338799
87	0.8318	-0.1103	-0.0893	2.0716	0.338798
88	0.8320	-0.1105	-0.0892	2.0716	0.338798
89	0.8322	-0.1105	-0.0891	2.0717	0.338797
90	0.8323	-0.1107	-0.0891	2.0717	0.338797
91	0.8324	-0.1109	-0.0890	2.0717	0.338796
92	0.8325	-0.1109	-0.0889	2.0718	0.338796
93	0.8327	-0.1110	-0.0889	2.0718	0.338796
94	0.8328	-0.1111	-0.0888	2.0718	0.338796
95	0.8329	-0.1113	-0.0888	2.0718	0.338795
96	0.8330	-0.1113	-0.0888	2.0719	0.338795
97	0.8330	-0.1115	-0.0888	2.0718	0.338795
98	0.8331	-0.1116	-0.0887	2.0718	0.338795
99	0.8332	-0.1116	-0.0887	2.0718	0.338795
100	0.8333	-0.1117	-0.0887	2.0719	0.338795
101	0.8334	-0.1117	-0.0886	2.0719	0.338794
102	0.8334	-0.1118	-0.0886	2.0719	0.338794
103	0.8335	-0.1119	-0.0886	2.0719	0.338794
104	0.8336	-0.1119	-0.0885	2.0719	0.338794
105	0.8336	-0.1120	-0.0885	2.0719	0.338794
106	0.8336	-0.1121	-0.0885	2.0719	0.338794
107	0.8337	-0.1121	-0.0885	2.0719	0.338794
108	0.8337	-0.1121	-0.0884	2.0719	0.338794
109	0.8338	-0.1121	-0.0884	2.0719	0.338794
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372	0.8346	-0.1128	-0.0881	2.0720	0.338794
373	0.8346	-0.1129	-0.0882	2.0720	0.338794
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378	0.8346	-0.1129	-0.0882	2.0719	0.338794
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393	0.8346	-0.1130	-0.0882	2.0719	0.338794
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397	0.8345	-0.1130	-0.0882	2.0719	0.338794
398	0.8345	-0.1131	-0.0882	2.0719	0.338794
399	0.8345	-0.1131	-0.0882	2.0719	0.338794
400	0.8345	-0.1131	-0.0882	2.0719	0.338794
401	0.8344	-0.1131	-0.0881	2.0719	0.338794
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403	0.8345	-0.1131	-0.0881	2.0719	0.338794
404	0.8346	-0.1130	-0.0881	2.0719	0.338794
405	0.8346	-0.1130	-0.0881	2.0718	0.338794
406	0.8346	-0.1129	-0.0881	2.0718	0.338794
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517	0.8346	-0.1126	-0.0880	2.0720	0.338794
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631	0.8346	-0.1127	-0.0881	2.0719	0.338794
632	0.8346	-0.1127	-0.0881	2.0719	0.338794
633	0.8346	-0.1128	-0.0881	2.0719	0.338794
634	0.8345	-0.1128	-0.0881	2.0719	0.338794
635	0.8346	-0.1127	-0.0881	2.0719	0.338794
636	0.8345	-0.1128	-0.0881	2.0719	0.338794
637	0.8345	-0.1128	-0.0881	2.0720	0.338794
638	0.8345	-0.1128	-0.0881	2.0720	0.338794
639	0.8345	-0.1127	-0.0881	2.0720	0.338794
640	0.8345	-0.1127	-0.0881	2.0720	0.338794
641	0.8346	-0.1127	-0.0881	2.0720	0.338794
642	0.8345	-0.1127	-0.0881	2.0720	0.338794
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644	0.8345	-0.1128	-0.0881	2.0720	0.338794
645	0.8345	-0.1128	-0.0881	2.0720	0.338794
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647	0.8344	-0.1129	-0.0881	2.0719	0.338794
648	0.8345	-0.1128	-0.0881	2.0719	0.338794
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650	0.8344	-0.1128	-0.0881	2.0719	0.338794
651	0.8345	-0.1128	-0.0881	2.0720	0.338794
652	0.8345	-0.1127	-0.0881	2.0719	0.338794
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658	0.8345	-0.1128	-0.0881	2.0719	0.338794
659	0.8345	-0.1128	-0.0881	2.0720	0.338794
660	0.8345	-0.1128	-0.0881	2.0720	0.338794
661	0.8345	-0.1127	-0.0881	2.0720	0.338794
662	0.8345	-0.1128	-0.0881	2.0720	0.338794
663	0.8345	-0.1128	-0.0881	2.0720	0.338794
664	0.8346	-0.1127	-0.0881	2.0720	0.338794
665	0.8346	-0.1127	-0.0881	2.0720	0.338794
666	0.8345	-0.1128	-0.0881	2.0720	0.338794
667	0.8345	-0.1128	-0.0882	2.0719	0.338794
668	0.8345	-0.1128	-0.0882	2.0719	0.338794
669	0.8345	-0.1129	-0.0882	2.0719	0.338794
670	0.8345	-0.1129	-0.0882	2.0719	0.338794

671	0.8346	-0.1129	-0.0882	2.0719	0.338794
672	0.8346	-0.1129	-0.0882	2.0720	0.338794
673	0.8346	-0.1129	-0.0882	2.0719	0.338794
674	0.8347	-0.1128	-0.0882	2.0719	0.338794
675	0.8346	-0.1129	-0.0882	2.0719	0.338794
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688	0.8347	-0.1128	-0.0882	2.0719	0.338794
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690	0.8347	-0.1129	-0.0882	2.0719	0.338794
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692	0.8346	-0.1130	-0.0882	2.0719	0.338794
693	0.8347	-0.1128	-0.0881	2.0719	0.338794
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696	0.8347	-0.1128	-0.0881	2.0720	0.338794
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698	0.8346	-0.1129	-0.0881	2.0720	0.338794
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702	0.8346	-0.1127	-0.0881	2.0719	0.338794
703	0.8346	-0.1128	-0.0881	2.0720	0.338794
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705	0.8346	-0.1128	-0.0881	2.0719	0.338794
706	0.8346	-0.1129	-0.0881	2.0719	0.338794
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708	0.8346	-0.1129	-0.0881	2.0720	0.338794
709	0.8346	-0.1128	-0.0881	2.0720	0.338794
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711	0.8346	-0.1129	-0.0881	2.0720	0.338794
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715	0.8346	-0.1129	-0.0881	2.0720	0.338794
716	0.8346	-0.1130	-0.0881	2.0720	0.338794
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719	0.8346	-0.1129	-0.0881	2.0719	0.338794
720	0.8346	-0.1130	-0.0881	2.0719	0.338794
721	0.8346	-0.1129	-0.0881	2.0719	0.338794
722	0.8346	-0.1129	-0.0881	2.0719	0.338794
723	0.8347	-0.1129	-0.0881	2.0719	0.338794
724	0.8347	-0.1128	-0.0881	2.0719	0.338794
725	0.8348	-0.1127	-0.0881	2.0719	0.338794
726	0.8347	-0.1128	-0.0881	2.0720	0.338794

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730	0.8347	-0.1128	-0.0881	2.0720	0.338794
731	0.8347	-0.1128	-0.0881	2.0720	0.338794
732	0.8347	-0.1127	-0.0881	2.0720	0.338794
733	0.8347	-0.1127	-0.0882	2.0720	0.338794
734	0.8346	-0.1128	-0.0882	2.0720	0.338794
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736	0.8346	-0.1129	-0.0882	2.0720	0.338794
737	0.8346	-0.1129	-0.0882	2.0720	0.338794
738	0.8346	-0.1130	-0.0882	2.0720	0.338794
739	0.8346	-0.1129	-0.0882	2.0720	0.338794
740	0.8345	-0.1130	-0.0881	2.0720	0.338794
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746	0.8345	-0.1130	-0.0882	2.0720	0.338794
747	0.8345	-0.1130	-0.0882	2.0719	0.338794
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749	0.8346	-0.1129	-0.0882	2.0719	0.338794
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764	0.8346	-0.1129	-0.0882	2.0720	0.338794
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769	0.8346	-0.1129	-0.0882	2.0720	0.338794
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771	0.8346	-0.1129	-0.0881	2.0720	0.338794
772	0.8346	-0.1129	-0.0881	2.0720	0.338794
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774	0.8346	-0.1128	-0.0881	2.0720	0.338794
775	0.8346	-0.1128	-0.0881	2.0720	0.338794
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778	0.8346	-0.1127	-0.0881	2.0719	0.338794
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780	0.8346	-0.1128	-0.0881	2.0720	0.338794
781	0.8345	-0.1128	-0.0881	2.0720	0.338794
782	0.8345	-0.1128	-0.0881	2.0719	0.338794

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784	0.8345	-0.1129	-0.0881	2.0719	0.338794
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787	0.8344	-0.1130	-0.0881	2.0719	0.338794
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790	0.8344	-0.1129	-0.0881	2.0719	0.338794
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799	0.8345	-0.1128	-0.0881	2.0719	0.338794
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812	0.8345	-0.1129	-0.0881	2.0720	0.338794
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816	0.8345	-0.1129	-0.0882	2.0720	0.338794
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818	0.8345	-0.1129	-0.0881	2.0719	0.338794
819	0.8346	-0.1129	-0.0881	2.0719	0.338794
820	0.8345	-0.1130	-0.0881	2.0719	0.338794
821	0.8345	-0.1130	-0.0881	2.0719	0.338794
822	0.8346	-0.1130	-0.0881	2.0720	0.338794
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825	0.8345	-0.1130	-0.0881	2.0720	0.338794
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830	0.8345	-0.1129	-0.0881	2.0720	0.338794
831	0.8346	-0.1129	-0.0881	2.0721	0.338794
832	0.8346	-0.1129	-0.0881	2.0721	0.338794
833	0.8346	-0.1129	-0.0881	2.0721	0.338794
834	0.8346	-0.1128	-0.0881	2.0720	0.338794
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838	0.8345	-0.1129	-0.0881	2.0720	0.338794

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840	0.8346	-0.1127	-0.0881	2.0720	0.338794
841	0.8346	-0.1127	-0.0881	2.0720	0.338794
842	0.8346	-0.1126	-0.0881	2.0720	0.338794
843	0.8346	-0.1127	-0.0880	2.0720	0.338794
844	0.8346	-0.1127	-0.0880	2.0720	0.338794
845	0.8345	-0.1128	-0.0881	2.0720	0.338794
846	0.8346	-0.1128	-0.0881	2.0720	0.338794
847	0.8346	-0.1127	-0.0881	2.0720	0.338794
848	0.8346	-0.1127	-0.0881	2.0720	0.338794
849	0.8346	-0.1127	-0.0881	2.0720	0.338794
850	0.8347	-0.1126	-0.0881	2.0720	0.338794
851	0.8347	-0.1126	-0.0881	2.0720	0.338794
852	0.8347	-0.1126	-0.0881	2.0721	0.338794
853	0.8347	-0.1126	-0.0881	2.0721	0.338794
854	0.8347	-0.1126	-0.0881	2.0720	0.338794
855	0.8346	-0.1126	-0.0881	2.0721	0.338794
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857	0.8346	-0.1128	-0.0881	2.0720	0.338794
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864	0.8346	-0.1128	-0.0881	2.0720	0.338794
865	0.8346	-0.1127	-0.0881	2.0720	0.338794
866	0.8346	-0.1127	-0.0881	2.0720	0.338794
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868	0.8346	-0.1126	-0.0881	2.0720	0.338794
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871	0.8346	-0.1128	-0.0881	2.0719	0.338794
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889	0.8346	-0.1128	-0.0881	2.0720	0.338794
890	0.8346	-0.1127	-0.0881	2.0719	0.338794
891	0.8346	-0.1127	-0.0881	2.0719	0.338794
892	0.8346	-0.1127	-0.0881	2.0720	0.338794
893	0.8346	-0.1127	-0.0881	2.0720	0.338794
894	0.8346	-0.1128	-0.0880	2.0719	0.338794

895	0.8345	-0.1128	-0.0880	2.0720	0.338794
896	0.8346	-0.1127	-0.0881	2.0720	0.338794
897	0.8345	-0.1128	-0.0881	2.0720	0.338794
898	0.8346	-0.1128	-0.0881	2.0720	0.338794
899	0.8346	-0.1128	-0.0881	2.0719	0.338794
900	0.8346	-0.1129	-0.0881	2.0720	0.338794
901	0.8346	-0.1129	-0.0881	2.0720	0.338794
902	0.8346	-0.1128	-0.0881	2.0719	0.338794
903	0.8347	-0.1127	-0.0881	2.0720	0.338794
904	0.8346	-0.1127	-0.0881	2.0720	0.338794
905	0.8346	-0.1127	-0.0881	2.0720	0.338794
906	0.8347	-0.1128	-0.0881	2.0720	0.338794
907	0.8346	-0.1128	-0.0881	2.0720	0.338794
908	0.8346	-0.1128	-0.0881	2.0720	0.338794
909	0.8346	-0.1128	-0.0881	2.0720	0.338794
910	0.8346	-0.1128	-0.0881	2.0720	0.338794
911	0.8346	-0.1129	-0.0881	2.0720	0.338794
912	0.8345	-0.1129	-0.0881	2.0720	0.338794
913	0.8345	-0.1129	-0.0881	2.0720	0.338794
914	0.8345	-0.1130	-0.0881	2.0720	0.338794
915	0.8346	-0.1129	-0.0881	2.0720	0.338794
916	0.8346	-0.1129	-0.0881	2.0720	0.338794
917	0.8346	-0.1128	-0.0881	2.0720	0.338794
918	0.8346	-0.1129	-0.0881	2.0720	0.338794
919	0.8345	-0.1129	-0.0882	2.0720	0.338794
920	0.8345	-0.1130	-0.0882	2.0720	0.338794
921	0.8345	-0.1130	-0.0881	2.0720	0.338794
922	0.8345	-0.1130	-0.0882	2.0720	0.338794
923	0.8345	-0.1130	-0.0882	2.0720	0.338794
924	0.8346	-0.1130	-0.0882	2.0719	0.338794
925	0.8346	-0.1130	-0.0882	2.0719	0.338794
926	0.8346	-0.1131	-0.0882	2.0719	0.338794
927	0.8345	-0.1131	-0.0882	2.0719	0.338794
928	0.8345	-0.1130	-0.0882	2.0720	0.338794
929	0.8345	-0.1130	-0.0882	2.0720	0.338794
930	0.8346	-0.1130	-0.0882	2.0720	0.338794
931	0.8346	-0.1130	-0.0882	2.0720	0.338794
932	0.8346	-0.1130	-0.0882	2.0720	0.338794
933	0.8346	-0.1130	-0.0882	2.0720	0.338794
934	0.8346	-0.1130	-0.0882	2.0720	0.338794
935	0.8345	-0.1130	-0.0882	2.0721	0.338794
936	0.8346	-0.1129	-0.0882	2.0720	0.338794
937	0.8346	-0.1129	-0.0882	2.0721	0.338794
938	0.8346	-0.1128	-0.0882	2.0720	0.338794
939	0.8346	-0.1128	-0.0882	2.0720	0.338794
940	0.8346	-0.1128	-0.0881	2.0720	0.338794
941	0.8347	-0.1128	-0.0881	2.0721	0.338794
942	0.8347	-0.1128	-0.0881	2.0720	0.338794
943	0.8347	-0.1128	-0.0881	2.0720	0.338794
944	0.8347	-0.1128	-0.0881	2.0720	0.338794
945	0.8347	-0.1128	-0.0881	2.0720	0.338794
946	0.8347	-0.1128	-0.0882	2.0720	0.338794
947	0.8347	-0.1128	-0.0882	2.0720	0.338794
948	0.8347	-0.1128	-0.0882	2.0720	0.338794
949	0.8347	-0.1128	-0.0882	2.0720	0.338794
950	0.8347	-0.1128	-0.0882	2.0720	0.338794

951	0.8347	-0.1128	-0.0882	2.0719	0.338794
952	0.8347	-0.1127	-0.0881	2.0719	0.338794
953	0.8347	-0.1127	-0.0881	2.0719	0.338794
954	0.8347	-0.1127	-0.0882	2.0719	0.338794
955	0.8346	-0.1129	-0.0882	2.0719	0.338794
956	0.8345	-0.1129	-0.0881	2.0719	0.338794
957	0.8345	-0.1129	-0.0882	2.0719	0.338794
958	0.8345	-0.1129	-0.0882	2.0720	0.338794
959	0.8346	-0.1129	-0.0882	2.0720	0.338794
960	0.8345	-0.1129	-0.0882	2.0720	0.338794
961	0.8345	-0.1129	-0.0882	2.0719	0.338794
962	0.8345	-0.1129	-0.0881	2.0719	0.338794
963	0.8345	-0.1129	-0.0881	2.0719	0.338794
964	0.8345	-0.1129	-0.0881	2.0720	0.338794
965	0.8345	-0.1129	-0.0881	2.0720	0.338794
966	0.8345	-0.1130	-0.0881	2.0720	0.338794
967	0.8345	-0.1130	-0.0881	2.0720	0.338794
968	0.8345	-0.1129	-0.0881	2.0719	0.338794
969	0.8345	-0.1129	-0.0881	2.0719	0.338794
970	0.8345	-0.1129	-0.0881	2.0719	0.338794
971	0.8345	-0.1129	-0.0881	2.0719	0.338794
972	0.8346	-0.1128	-0.0881	2.0719	0.338794
973	0.8346	-0.1128	-0.0881	2.0719	0.338794
974	0.8346	-0.1129	-0.0881	2.0719	0.338794
975	0.8346	-0.1129	-0.0881	2.0720	0.338794
976	0.8346	-0.1128	-0.0881	2.0719	0.338794
977	0.8346	-0.1128	-0.0881	2.0720	0.338794
978	0.8345	-0.1129	-0.0882	2.0720	0.338794
979	0.8345	-0.1130	-0.0882	2.0719	0.338794
980	0.8345	-0.1129	-0.0881	2.0720	0.338794
981	0.8345	-0.1129	-0.0881	2.0719	0.338794
982	0.8345	-0.1129	-0.0881	2.0719	0.338794
983	0.8346	-0.1128	-0.0881	2.0719	0.338794
984	0.8346	-0.1128	-0.0881	2.0719	0.338794
985	0.8345	-0.1128	-0.0881	2.0719	0.338794
986	0.8346	-0.1128	-0.0881	2.0719	0.338794
987	0.8345	-0.1128	-0.0881	2.0719	0.338794
988	0.8346	-0.1128	-0.0881	2.0719	0.338794
989	0.8346	-0.1128	-0.0881	2.0719	0.338794
990	0.8345	-0.1129	-0.0881	2.0720	0.338794
991	0.8346	-0.1128	-0.0881	2.0720	0.338794
992	0.8346	-0.1128	-0.0881	2.0720	0.338794
993	0.8346	-0.1127	-0.0881	2.0719	0.338794
994	0.8346	-0.1127	-0.0881	2.0719	0.338794
995	0.8346	-0.1127	-0.0881	2.0719	0.338794
996	0.8346	-0.1128	-0.0881	2.0719	0.338794
997	0.8346	-0.1128	-0.0881	2.0719	0.338794
998	0.8346	-0.1128	-0.0881	2.0719	0.338794
999	0.8346	-0.1128	-0.0881	2.0719	0.338794
1000	0.8346	-0.1128	-0.0881	2.0719	0.338794

Mini-Batch 20% Convergence

Iteration	w1	w2	w3	b	J(w,b)
1	0.0391	0.0092	-0.0081	0.1016	2.576309
2	0.0760	0.0172	-0.0156	0.1981	2.361094
3	0.1110	0.0243	-0.0228	0.2900	2.166879

4	0.1441	0.0304	-0.0294	0.3773	1.991642
5	0.1754	0.0356	-0.0357	0.4604	1.833460
6	0.2051	0.0401	-0.0416	0.5394	1.690655
7	0.2333	0.0438	-0.0471	0.6145	1.561710
8	0.2600	0.0469	-0.0522	0.6859	1.445261
9	0.2853	0.0494	-0.0570	0.7539	1.340086
10	0.3093	0.0513	-0.0615	0.8185	1.245082
11	0.3320	0.0527	-0.0657	0.8799	1.159248
12	0.3537	0.0536	-0.0696	0.9383	1.081673
13	0.3742	0.0541	-0.0732	0.9939	1.011576
14	0.3937	0.0542	-0.0766	1.0467	0.948203
15	0.4122	0.0540	-0.0798	1.0970	0.890917
16	0.4299	0.0535	-0.0827	1.1448	0.839106
17	0.4466	0.0528	-0.0854	1.1902	0.792245
18	0.4626	0.0517	-0.0880	1.2334	0.749863
19	0.4778	0.0505	-0.0903	1.2745	0.711523
20	0.4922	0.0490	-0.0924	1.3136	0.676831
21	0.5060	0.0474	-0.0944	1.3508	0.645428
22	0.5191	0.0455	-0.0962	1.3861	0.617006
23	0.5316	0.0436	-0.0979	1.4198	0.591277
24	0.5435	0.0415	-0.0995	1.4517	0.567981
25	0.5549	0.0393	-0.1009	1.4821	0.546878
26	0.5657	0.0371	-0.1021	1.5110	0.527765
27	0.5761	0.0347	-0.1033	1.5385	0.510450
28	0.5860	0.0323	-0.1044	1.5647	0.494760
29	0.5954	0.0298	-0.1053	1.5895	0.480539
30	0.6044	0.0273	-0.1062	1.6132	0.467647
31	0.6131	0.0248	-0.1070	1.6357	0.455961
32	0.6213	0.0222	-0.1076	1.6571	0.445363
33	0.6292	0.0196	-0.1083	1.6774	0.435751
34	0.6368	0.0170	-0.1088	1.6967	0.427032
35	0.6440	0.0143	-0.1092	1.7151	0.419120
36	0.6509	0.0117	-0.1096	1.7326	0.411940
37	0.6575	0.0091	-0.1100	1.7492	0.405423
38	0.6639	0.0065	-0.1102	1.7651	0.399502
39	0.6699	0.0039	-0.1105	1.7801	0.394129
40	0.6758	0.0013	-0.1107	1.7944	0.389245
41	0.6814	-0.0012	-0.1108	1.8080	0.384807
42	0.6867	-0.0038	-0.1109	1.8209	0.380773
43	0.6919	-0.0063	-0.1109	1.8332	0.377105
44	0.6968	-0.0088	-0.1110	1.8449	0.373772
45	0.7016	-0.0112	-0.1109	1.8561	0.370739
46	0.7061	-0.0137	-0.1109	1.8666	0.367981
47	0.7105	-0.0160	-0.1108	1.8767	0.365469
48	0.7147	-0.0184	-0.1107	1.8863	0.363183
49	0.7188	-0.0207	-0.1106	1.8954	0.361101
50	0.7227	-0.0229	-0.1105	1.9040	0.359204
51	0.7264	-0.0251	-0.1103	1.9123	0.357476
52	0.7300	-0.0273	-0.1101	1.9201	0.355902
53	0.7335	-0.0295	-0.1099	1.9275	0.354466
54	0.7369	-0.0316	-0.1097	1.9346	0.353156
55	0.7401	-0.0337	-0.1095	1.9414	0.351961
56	0.7432	-0.0357	-0.1092	1.9478	0.350870
57	0.7462	-0.0377	-0.1090	1.9539	0.349876
58	0.7490	-0.0396	-0.1087	1.9596	0.348968
59	0.7518	-0.0415	-0.1084	1.9651	0.348139

60	0.7545	-0.0434	-0.1081	1.9704	0.347380
61	0.7570	-0.0452	-0.1078	1.9754	0.346688
62	0.7595	-0.0470	-0.1075	1.9801	0.346054
63	0.7619	-0.0487	-0.1072	1.9846	0.345473
64	0.7642	-0.0504	-0.1069	1.9889	0.344943
65	0.7665	-0.0521	-0.1066	1.9929	0.344456
66	0.7686	-0.0537	-0.1063	1.9968	0.344011
67	0.7707	-0.0553	-0.1060	2.0005	0.343603
68	0.7727	-0.0569	-0.1057	2.0040	0.343228
69	0.7746	-0.0584	-0.1054	2.0073	0.342885
70	0.7765	-0.0598	-0.1051	2.0105	0.342570
71	0.7783	-0.0613	-0.1048	2.0135	0.342282
72	0.7801	-0.0627	-0.1044	2.0164	0.342016
73	0.7818	-0.0640	-0.1041	2.0191	0.341773
74	0.7834	-0.0654	-0.1038	2.0217	0.341548
75	0.7850	-0.0667	-0.1035	2.0242	0.341342
76	0.7865	-0.0679	-0.1032	2.0265	0.341153
77	0.7880	-0.0692	-0.1029	2.0287	0.340978
78	0.7894	-0.0704	-0.1026	2.0309	0.340818
79	0.7908	-0.0715	-0.1023	2.0329	0.340670
80	0.7921	-0.0727	-0.1020	2.0348	0.340533
81	0.7934	-0.0738	-0.1017	2.0366	0.340407
82	0.7947	-0.0749	-0.1014	2.0383	0.340292
83	0.7959	-0.0759	-0.1011	2.0400	0.340185
84	0.7970	-0.0770	-0.1008	2.0415	0.340086
85	0.7982	-0.0780	-0.1006	2.0430	0.339995
86	0.7993	-0.0789	-0.1003	2.0445	0.339910
87	0.8003	-0.0799	-0.1000	2.0458	0.339832
88	0.8014	-0.0808	-0.0997	2.0471	0.339760
89	0.8024	-0.0817	-0.0995	2.0483	0.339693
90	0.8033	-0.0826	-0.0992	2.0495	0.339631
91	0.8042	-0.0834	-0.0990	2.0506	0.339574
92	0.8052	-0.0842	-0.0987	2.0516	0.339521
93	0.8060	-0.0851	-0.0985	2.0526	0.339472
94	0.8069	-0.0859	-0.0982	2.0536	0.339426
95	0.8077	-0.0866	-0.0980	2.0545	0.339384
96	0.8085	-0.0873	-0.0978	2.0553	0.339344
97	0.8093	-0.0881	-0.0975	2.0561	0.339308
98	0.8100	-0.0888	-0.0973	2.0569	0.339274
99	0.8108	-0.0894	-0.0971	2.0577	0.339242
100	0.8115	-0.0901	-0.0969	2.0584	0.339213
101	0.8121	-0.0907	-0.0966	2.0590	0.339186
102	0.8128	-0.0914	-0.0964	2.0597	0.339160
103	0.8134	-0.0920	-0.0962	2.0603	0.339137
104	0.8141	-0.0926	-0.0960	2.0608	0.339115
105	0.8147	-0.0931	-0.0958	2.0614	0.339094
106	0.8152	-0.0937	-0.0957	2.0619	0.339075
107	0.8158	-0.0943	-0.0955	2.0624	0.339057
108	0.8164	-0.0948	-0.0953	2.0629	0.339041
109	0.8169	-0.0953	-0.0951	2.0633	0.339025
110	0.8174	-0.0958	-0.0949	2.0637	0.339011
111	0.8179	-0.0963	-0.0948	2.0641	0.338997
112	0.8184	-0.0967	-0.0946	2.0645	0.338984
113	0.8189	-0.0972	-0.0944	2.0649	0.338973
114	0.8194	-0.0976	-0.0943	2.0652	0.338962
115	0.8198	-0.0981	-0.0941	2.0656	0.338951

116	0.8202	-0.0985	-0.0939	2.0659	0.338942
117	0.8206	-0.0989	-0.0938	2.0662	0.338933
118	0.8210	-0.0993	-0.0937	2.0664	0.338924
119	0.8214	-0.0997	-0.0935	2.0667	0.338916
120	0.8218	-0.1001	-0.0934	2.0670	0.338909
121	0.8222	-0.1004	-0.0932	2.0672	0.338902
122	0.8225	-0.1008	-0.0931	2.0674	0.338896
123	0.8229	-0.1011	-0.0930	2.0677	0.338889
124	0.8232	-0.1014	-0.0928	2.0679	0.338884
125	0.8236	-0.1018	-0.0927	2.0681	0.338878
126	0.8239	-0.1021	-0.0926	2.0682	0.338873
127	0.8242	-0.1024	-0.0925	2.0684	0.338869
128	0.8245	-0.1027	-0.0924	2.0686	0.338864
129	0.8248	-0.1030	-0.0923	2.0688	0.338860
130	0.8251	-0.1033	-0.0922	2.0689	0.338856
131	0.8253	-0.1035	-0.0920	2.0691	0.338852
132	0.8256	-0.1038	-0.0919	2.0692	0.338849
133	0.8259	-0.1041	-0.0918	2.0693	0.338846
134	0.8261	-0.1043	-0.0917	2.0695	0.338842
135	0.8263	-0.1046	-0.0916	2.0696	0.338840
136	0.8266	-0.1048	-0.0915	2.0697	0.338837
137	0.8268	-0.1051	-0.0915	2.0698	0.338834
138	0.8271	-0.1053	-0.0914	2.0699	0.338832
139	0.8273	-0.1055	-0.0913	2.0700	0.338830
140	0.8275	-0.1057	-0.0912	2.0701	0.338828
141	0.8277	-0.1059	-0.0911	2.0702	0.338826
142	0.8279	-0.1061	-0.0910	2.0703	0.338824
143	0.8281	-0.1063	-0.0910	2.0704	0.338822
144	0.8283	-0.1064	-0.0909	2.0704	0.338821
145	0.8285	-0.1066	-0.0908	2.0705	0.338819
146	0.8286	-0.1068	-0.0907	2.0706	0.338818
147	0.8288	-0.1070	-0.0907	2.0706	0.338816
148	0.8290	-0.1072	-0.0906	2.0707	0.338815
149	0.8291	-0.1074	-0.0905	2.0708	0.338814
150	0.8293	-0.1075	-0.0905	2.0708	0.338812
151	0.8294	-0.1077	-0.0904	2.0709	0.338811
152	0.8296	-0.1078	-0.0903	2.0709	0.338810
153	0.8297	-0.1080	-0.0903	2.0710	0.338809
154	0.8299	-0.1081	-0.0902	2.0710	0.338808
155	0.8300	-0.1083	-0.0902	2.0711	0.338808
156	0.8301	-0.1084	-0.0901	2.0711	0.338807
157	0.8303	-0.1085	-0.0901	2.0712	0.338806
158	0.8304	-0.1087	-0.0900	2.0712	0.338805
159	0.8305	-0.1088	-0.0900	2.0712	0.338805
160	0.8306	-0.1089	-0.0899	2.0713	0.338804
161	0.8307	-0.1090	-0.0899	2.0713	0.338803
162	0.8308	-0.1091	-0.0898	2.0713	0.338803
163	0.8309	-0.1092	-0.0898	2.0714	0.338802
164	0.8310	-0.1093	-0.0897	2.0714	0.338802
165	0.8311	-0.1094	-0.0897	2.0714	0.338801
166	0.8312	-0.1095	-0.0896	2.0714	0.338801
167	0.8313	-0.1096	-0.0896	2.0715	0.338800
168	0.8314	-0.1097	-0.0895	2.0715	0.338800
169	0.8315	-0.1098	-0.0895	2.0715	0.338800
170	0.8316	-0.1099	-0.0895	2.0716	0.338799
171	0.8317	-0.1100	-0.0894	2.0716	0.338799

172	0.8318	-0.1100	-0.0894	2.0716	0.338799
173	0.8319	-0.1101	-0.0893	2.0716	0.338798
174	0.8320	-0.1102	-0.0893	2.0716	0.338798
175	0.8320	-0.1103	-0.0893	2.0716	0.338798
176	0.8321	-0.1104	-0.0892	2.0717	0.338798
177	0.8322	-0.1104	-0.0892	2.0717	0.338797
178	0.8322	-0.1105	-0.0892	2.0717	0.338797
179	0.8323	-0.1106	-0.0892	2.0717	0.338797
180	0.8324	-0.1107	-0.0891	2.0717	0.338797
181	0.8324	-0.1107	-0.0891	2.0717	0.338797
182	0.8325	-0.1108	-0.0891	2.0717	0.338796
183	0.8326	-0.1108	-0.0890	2.0717	0.338796
184	0.8326	-0.1109	-0.0890	2.0718	0.338796
185	0.8327	-0.1109	-0.0890	2.0718	0.338796
186	0.8327	-0.1110	-0.0890	2.0718	0.338796
187	0.8328	-0.1111	-0.0890	2.0718	0.338796
188	0.8328	-0.1111	-0.0889	2.0718	0.338796
189	0.8328	-0.1112	-0.0889	2.0718	0.338795
190	0.8329	-0.1113	-0.0889	2.0718	0.338795
191	0.8329	-0.1113	-0.0889	2.0718	0.338795
192	0.8330	-0.1114	-0.0889	2.0718	0.338795
193	0.8330	-0.1114	-0.0888	2.0718	0.338795
194	0.8331	-0.1115	-0.0888	2.0718	0.338795
195	0.8331	-0.1115	-0.0888	2.0718	0.338795
196	0.8332	-0.1115	-0.0888	2.0718	0.338795
197	0.8332	-0.1116	-0.0888	2.0718	0.338795
198	0.8333	-0.1116	-0.0887	2.0718	0.338795
199	0.8333	-0.1116	-0.0887	2.0718	0.338795
200	0.8334	-0.1117	-0.0887	2.0719	0.338795
201	0.8334	-0.1117	-0.0887	2.0719	0.338795
202	0.8334	-0.1117	-0.0887	2.0719	0.338794
203	0.8335	-0.1118	-0.0887	2.0719	0.338794
204	0.8335	-0.1118	-0.0886	2.0719	0.338794
205	0.8335	-0.1118	-0.0886	2.0719	0.338794
206	0.8336	-0.1119	-0.0886	2.0719	0.338794
207	0.8336	-0.1119	-0.0886	2.0719	0.338794
208	0.8336	-0.1119	-0.0886	2.0719	0.338794
209	0.8336	-0.1119	-0.0886	2.0719	0.338794
210	0.8337	-0.1120	-0.0886	2.0719	0.338794
211	0.8337	-0.1120	-0.0885	2.0719	0.338794
212	0.8337	-0.1120	-0.0885	2.0719	0.338794
213	0.8337	-0.1121	-0.0885	2.0719	0.338794
214	0.8338	-0.1121	-0.0885	2.0719	0.338794
215	0.8338	-0.1121	-0.0885	2.0719	0.338794
216	0.8338	-0.1121	-0.0885	2.0719	0.338794
217	0.8339	-0.1121	-0.0885	2.0719	0.338794
218	0.8339	-0.1122	-0.0885	2.0719	0.338794
219	0.8339	-0.1122	-0.0885	2.0719	0.338794
220	0.8339	-0.1122	-0.0885	2.0719	0.338794
221	0.8339	-0.1122	-0.0884	2.0719	0.338794
222	0.8339	-0.1123	-0.0884	2.0719	0.338794
223	0.8339	-0.1123	-0.0884	2.0719	0.338794
224	0.8340	-0.1123	-0.0884	2.0719	0.338794
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227	0.8340	-0.1123	-0.0884	2.0719	0.338794

228	0.8340	-0.1124	-0.0884	2.0719	0.338794
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230	0.8341	-0.1124	-0.0884	2.0719	0.338794
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232	0.8341	-0.1124	-0.0884	2.0719	0.338794
233	0.8341	-0.1124	-0.0884	2.0719	0.338794
234	0.8341	-0.1124	-0.0883	2.0719	0.338794
235	0.8342	-0.1124	-0.0883	2.0719	0.338794
236	0.8342	-0.1124	-0.0883	2.0719	0.338794
237	0.8342	-0.1125	-0.0883	2.0719	0.338794
238	0.8342	-0.1124	-0.0883	2.0719	0.338794
239	0.8342	-0.1124	-0.0883	2.0719	0.338794
240	0.8342	-0.1125	-0.0883	2.0719	0.338794
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250	0.8343	-0.1126	-0.0883	2.0720	0.338794
251	0.8343	-0.1126	-0.0883	2.0719	0.338794
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254	0.8343	-0.1127	-0.0883	2.0719	0.338794
255	0.8343	-0.1126	-0.0882	2.0719	0.338794
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257	0.8343	-0.1127	-0.0882	2.0719	0.338794
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267	0.8344	-0.1128	-0.0882	2.0719	0.338794
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270	0.8344	-0.1128	-0.0882	2.0720	0.338794
271	0.8344	-0.1128	-0.0882	2.0720	0.338794
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273	0.8344	-0.1128	-0.0882	2.0720	0.338794
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285	0.8345	-0.1128	-0.0882	2.0720	0.338794
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325	0.8346	-0.1128	-0.0881	2.0720	0.338794
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679	0.8346	-0.1128	-0.0881	2.0719	0.338794
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682	0.8346	-0.1129	-0.0881	2.0720	0.338794
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936	0.8346	-0.1129	-0.0881	2.0720	0.338794
937	0.8346	-0.1129	-0.0881	2.0720	0.338794
938	0.8346	-0.1129	-0.0881	2.0720	0.338794
939	0.8346	-0.1129	-0.0881	2.0720	0.338794
940	0.8346	-0.1129	-0.0881	2.0720	0.338794
941	0.8346	-0.1129	-0.0881	2.0720	0.338794
942	0.8346	-0.1129	-0.0881	2.0719	0.338794
943	0.8346	-0.1129	-0.0881	2.0719	0.338794
944	0.8346	-0.1129	-0.0881	2.0719	0.338794
945	0.8346	-0.1129	-0.0881	2.0719	0.338794
946	0.8346	-0.1129	-0.0881	2.0719	0.338794
947	0.8346	-0.1129	-0.0881	2.0720	0.338794
948	0.8346	-0.1129	-0.0881	2.0720	0.338794
949	0.8346	-0.1129	-0.0881	2.0719	0.338794
950	0.8346	-0.1129	-0.0881	2.0719	0.338794
951	0.8346	-0.1129	-0.0881	2.0719	0.338794
952	0.8346	-0.1129	-0.0881	2.0719	0.338794
953	0.8346	-0.1129	-0.0881	2.0719	0.338794
954	0.8346	-0.1129	-0.0881	2.0719	0.338794
955	0.8346	-0.1129	-0.0881	2.0719	0.338794

```
 956     0.8346    -0.1129    -0.0881     2.0719         0.338794
 957     0.8346    -0.1129    -0.0881     2.0719         0.338794
 958     0.8346    -0.1129    -0.0881     2.0719         0.338794
 959     0.8346    -0.1129    -0.0881     2.0719         0.338794
 960     0.8346    -0.1129    -0.0881     2.0719         0.338794
 961     0.8346    -0.1129    -0.0881     2.0719         0.338794
 962     0.8346    -0.1129    -0.0881     2.0719         0.338794
 963     0.8346    -0.1129    -0.0881     2.0719         0.338794
 964     0.8346    -0.1129    -0.0881     2.0719         0.338794
 965     0.8346    -0.1129    -0.0881     2.0719         0.338794
 966     0.8346    -0.1129    -0.0881     2.0719         0.338794
 967     0.8346    -0.1129    -0.0881     2.0719         0.338794
 968     0.8346    -0.1129    -0.0881     2.0719         0.338794
 969     0.8346    -0.1129    -0.0881     2.0719         0.338794
 970     0.8346    -0.1129    -0.0881     2.0719         0.338794
 971     0.8346    -0.1129    -0.0881     2.0719         0.338794
 972     0.8345    -0.1129    -0.0881     2.0719         0.338794
 973     0.8345    -0.1129    -0.0881     2.0719         0.338794
 974     0.8345    -0.1129    -0.0881     2.0719         0.338794
 975     0.8345    -0.1129    -0.0881     2.0719         0.338794
 976     0.8346    -0.1129    -0.0881     2.0719         0.338794
 977     0.8346    -0.1129    -0.0882     2.0719         0.338794
 978     0.8346    -0.1129    -0.0882     2.0719         0.338794
 979     0.8346    -0.1129    -0.0882     2.0719         0.338794
 980     0.8346    -0.1129    -0.0881     2.0719         0.338794
 981     0.8346    -0.1129    -0.0881     2.0719         0.338794
 982     0.8346    -0.1129    -0.0881     2.0719         0.338794
 983     0.8346    -0.1129    -0.0881     2.0719         0.338794
 984     0.8346    -0.1129    -0.0881     2.0719         0.338794
 985     0.8346    -0.1129    -0.0881     2.0719         0.338794
 986     0.8346    -0.1129    -0.0881     2.0719         0.338794
 987     0.8346    -0.1129    -0.0882     2.0719         0.338794
 988     0.8346    -0.1129    -0.0882     2.0719         0.338794
 989     0.8346    -0.1129    -0.0881     2.0719         0.338794
 990     0.8346    -0.1129    -0.0881     2.0719         0.338794
 991     0.8346    -0.1129    -0.0881     2.0719         0.338794
 992     0.8346    -0.1129    -0.0881     2.0719         0.338794
 993     0.8346    -0.1129    -0.0881     2.0719         0.338794
 994     0.8346    -0.1129    -0.0882     2.0719         0.338794
 995     0.8346    -0.1129    -0.0881     2.0719         0.338794
 996     0.8346    -0.1129    -0.0882     2.0719         0.338794
 997     0.8346    -0.1129    -0.0881     2.0719         0.338794
 998     0.8346    -0.1129    -0.0881     2.0719         0.338794
 999     0.8346    -0.1129    -0.0881     2.0719         0.338794
1000     0.8346    -0.1129    -0.0881     2.0719         0.338794

Mini-Batch 25% Convergence
Iteration        w1         w2         w3          b           J(w,b)
        1    0.0314     0.0075    -0.0065     0.0816         2.622075
        2    0.0615     0.0142    -0.0127     0.1601         2.444535
        3    0.0902     0.0202    -0.0185     0.2354         2.281029
        4    0.1177     0.0257    -0.0241     0.3078         2.130426
        5    0.1441     0.0305    -0.0294     0.3773         1.991675
        6    0.1693     0.0348    -0.0345     0.4441         1.863847
        7    0.1934     0.0385    -0.0392     0.5082         1.746073
        8    0.2166     0.0418    -0.0438     0.5698         1.637543
```

9	0.2387	0.0446	-0.0481	0.6290	1.537530
10	0.2599	0.0470	-0.0522	0.6859	1.445340
11	0.2803	0.0490	-0.0560	0.7405	1.360365
12	0.2998	0.0506	-0.0597	0.7930	1.282016
13	0.3185	0.0519	-0.0632	0.8434	1.209788
14	0.3364	0.0530	-0.0665	0.8918	1.143183
15	0.3537	0.0537	-0.0696	0.9383	1.081764
16	0.3702	0.0541	-0.0725	0.9829	1.025115
17	0.3860	0.0543	-0.0753	1.0259	0.972863
18	0.4012	0.0543	-0.0779	1.0671	0.924668
19	0.4158	0.0541	-0.0804	1.1067	0.880207
20	0.4298	0.0536	-0.0827	1.1447	0.839184
21	0.4433	0.0530	-0.0849	1.1812	0.801327
22	0.4563	0.0522	-0.0870	1.2163	0.766385
23	0.4687	0.0513	-0.0889	1.2501	0.734141
24	0.4807	0.0502	-0.0907	1.2824	0.704376
25	0.4922	0.0491	-0.0924	1.3135	0.676897
26	0.5032	0.0477	-0.0940	1.3434	0.651528
27	0.5139	0.0463	-0.0955	1.3721	0.628101
28	0.5241	0.0448	-0.0969	1.3997	0.606465
29	0.5340	0.0432	-0.0982	1.4262	0.586481
30	0.5435	0.0416	-0.0994	1.4517	0.568029
31	0.5526	0.0399	-0.1006	1.4761	0.550980
32	0.5614	0.0381	-0.1016	1.4996	0.535231
33	0.5699	0.0362	-0.1026	1.5221	0.520678
34	0.5781	0.0343	-0.1035	1.5438	0.507233
35	0.5859	0.0324	-0.1044	1.5646	0.494801
36	0.5935	0.0304	-0.1051	1.5846	0.483315
37	0.6008	0.0284	-0.1058	1.6038	0.472691
38	0.6079	0.0263	-0.1065	1.6223	0.462873
39	0.6147	0.0243	-0.1071	1.6400	0.453795
40	0.6213	0.0222	-0.1076	1.6570	0.445398
41	0.6276	0.0201	-0.1081	1.6733	0.437635
42	0.6337	0.0180	-0.1086	1.6890	0.430454
43	0.6396	0.0160	-0.1090	1.7041	0.423807
44	0.6453	0.0139	-0.1093	1.7186	0.417658
45	0.6508	0.0118	-0.1096	1.7325	0.411967
46	0.6562	0.0096	-0.1099	1.7459	0.406701
47	0.6613	0.0076	-0.1101	1.7588	0.401824
48	0.6663	0.0055	-0.1104	1.7711	0.397309
49	0.6711	0.0034	-0.1105	1.7830	0.393130
50	0.6757	0.0013	-0.1107	1.7944	0.389259
51	0.6802	-0.0007	-0.1108	1.8053	0.385675
52	0.6846	-0.0027	-0.1109	1.8158	0.382355
53	0.6888	-0.0048	-0.1109	1.8259	0.379278
54	0.6929	-0.0068	-0.1109	1.8356	0.376426
55	0.6968	-0.0087	-0.1110	1.8449	0.373782
56	0.7006	-0.0107	-0.1109	1.8539	0.371332
57	0.7043	-0.0126	-0.1109	1.8624	0.369061
58	0.7079	-0.0146	-0.1109	1.8707	0.366955
59	0.7114	-0.0165	-0.1108	1.8786	0.365003
60	0.7147	-0.0183	-0.1107	1.8862	0.363191
61	0.7180	-0.0202	-0.1106	1.8936	0.361510
62	0.7211	-0.0220	-0.1105	1.9006	0.359950
63	0.7242	-0.0238	-0.1104	1.9073	0.358502
64	0.7272	-0.0256	-0.1103	1.9138	0.357158

65	0.7300	-0.0273	-0.1101	1.9201	0.355910
66	0.7328	-0.0290	-0.1099	1.9260	0.354750
67	0.7355	-0.0307	-0.1098	1.9318	0.353674
68	0.7381	-0.0324	-0.1096	1.9373	0.352674
69	0.7407	-0.0341	-0.1094	1.9426	0.351745
70	0.7431	-0.0357	-0.1092	1.9477	0.350881
71	0.7455	-0.0373	-0.1090	1.9526	0.350077
72	0.7479	-0.0388	-0.1088	1.9573	0.349329
73	0.7501	-0.0404	-0.1086	1.9618	0.348635
74	0.7523	-0.0419	-0.1084	1.9662	0.347988
75	0.7544	-0.0434	-0.1081	1.9703	0.347386
76	0.7565	-0.0448	-0.1079	1.9743	0.346825
77	0.7585	-0.0463	-0.1077	1.9782	0.346304
78	0.7605	-0.0477	-0.1074	1.9819	0.345819
79	0.7624	-0.0491	-0.1072	1.9854	0.345366
80	0.7642	-0.0504	-0.1070	1.9889	0.344945
81	0.7660	-0.0518	-0.1067	1.9921	0.344552
82	0.7677	-0.0531	-0.1065	1.9953	0.344186
83	0.7694	-0.0544	-0.1062	1.9983	0.343846
84	0.7711	-0.0556	-0.1060	2.0012	0.343528
85	0.7727	-0.0569	-0.1057	2.0040	0.343231
86	0.7742	-0.0581	-0.1055	2.0067	0.342954
87	0.7757	-0.0593	-0.1052	2.0092	0.342695
88	0.7772	-0.0604	-0.1050	2.0117	0.342454
89	0.7786	-0.0616	-0.1047	2.0141	0.342228
90	0.7800	-0.0627	-0.1045	2.0164	0.342018
91	0.7814	-0.0638	-0.1042	2.0186	0.341821
92	0.7827	-0.0648	-0.1040	2.0207	0.341637
93	0.7840	-0.0659	-0.1037	2.0227	0.341465
94	0.7853	-0.0669	-0.1035	2.0246	0.341304
95	0.7865	-0.0679	-0.1032	2.0265	0.341154
96	0.7877	-0.0689	-0.1030	2.0283	0.341013
97	0.7888	-0.0699	-0.1028	2.0300	0.340881
98	0.7899	-0.0709	-0.1025	2.0317	0.340758
99	0.7910	-0.0718	-0.1023	2.0332	0.340643
100	0.7921	-0.0727	-0.1020	2.0348	0.340535
101	0.7931	-0.0736	-0.1018	2.0362	0.340433
102	0.7941	-0.0744	-0.1016	2.0376	0.340338
103	0.7951	-0.0753	-0.1013	2.0390	0.340249
104	0.7961	-0.0761	-0.1011	2.0403	0.340166
105	0.7970	-0.0770	-0.1009	2.0415	0.340087
106	0.7979	-0.0778	-0.1007	2.0427	0.340013
107	0.7988	-0.0785	-0.1004	2.0439	0.339944
108	0.7997	-0.0793	-0.1002	2.0450	0.339879
109	0.8005	-0.0801	-0.1000	2.0460	0.339818
110	0.8013	-0.0808	-0.0998	2.0471	0.339761
111	0.8021	-0.0815	-0.0996	2.0480	0.339707
112	0.8029	-0.0822	-0.0994	2.0490	0.339657
113	0.8037	-0.0829	-0.0992	2.0499	0.339609
114	0.8044	-0.0836	-0.0990	2.0508	0.339565
115	0.8051	-0.0843	-0.0988	2.0516	0.339522
116	0.8058	-0.0849	-0.0986	2.0524	0.339483
117	0.8065	-0.0855	-0.0984	2.0532	0.339445
118	0.8072	-0.0861	-0.0982	2.0539	0.339410
119	0.8079	-0.0867	-0.0980	2.0546	0.339377
120	0.8085	-0.0873	-0.0978	2.0553	0.339345

121	0.8091	-0.0879	-0.0976	2.0559	0.339316
122	0.8097	-0.0885	-0.0974	2.0566	0.339288
123	0.8103	-0.0890	-0.0972	2.0572	0.339262
124	0.8109	-0.0896	-0.0971	2.0578	0.339237
125	0.8114	-0.0901	-0.0969	2.0583	0.339214
126	0.8120	-0.0906	-0.0967	2.0589	0.339192
127	0.8125	-0.0911	-0.0965	2.0594	0.339171
128	0.8130	-0.0916	-0.0964	2.0599	0.339152
129	0.8136	-0.0921	-0.0962	2.0604	0.339133
130	0.8141	-0.0925	-0.0961	2.0608	0.339116
131	0.8145	-0.0930	-0.0959	2.0612	0.339099
132	0.8150	-0.0934	-0.0957	2.0617	0.339083
133	0.8155	-0.0939	-0.0956	2.0621	0.339068
134	0.8159	-0.0943	-0.0954	2.0625	0.339054
135	0.8164	-0.0947	-0.0953	2.0628	0.339041
136	0.8168	-0.0952	-0.0951	2.0632	0.339029
137	0.8172	-0.0956	-0.0950	2.0635	0.339017
138	0.8176	-0.0960	-0.0949	2.0639	0.339005
139	0.8180	-0.0964	-0.0947	2.0642	0.338995
140	0.8184	-0.0967	-0.0946	2.0645	0.338985
141	0.8188	-0.0971	-0.0945	2.0648	0.338975
142	0.8192	-0.0974	-0.0943	2.0651	0.338966
143	0.8195	-0.0978	-0.0942	2.0653	0.338958
144	0.8199	-0.0982	-0.0941	2.0656	0.338950
145	0.8202	-0.0985	-0.0940	2.0658	0.338942
146	0.8205	-0.0988	-0.0938	2.0661	0.338935
147	0.8209	-0.0992	-0.0937	2.0663	0.338928
148	0.8212	-0.0995	-0.0936	2.0665	0.338921
149	0.8215	-0.0998	-0.0935	2.0667	0.338915
150	0.8218	-0.1001	-0.0934	2.0670	0.338909
151	0.8221	-0.1004	-0.0933	2.0671	0.338903
152	0.8224	-0.1006	-0.0932	2.0673	0.338898
153	0.8227	-0.1009	-0.0931	2.0675	0.338893
154	0.8230	-0.1012	-0.0929	2.0677	0.338888
155	0.8232	-0.1015	-0.0928	2.0679	0.338884
156	0.8235	-0.1017	-0.0927	2.0680	0.338879
157	0.8237	-0.1020	-0.0926	2.0682	0.338875
158	0.8240	-0.1022	-0.0925	2.0683	0.338871
159	0.8242	-0.1025	-0.0925	2.0685	0.338867
160	0.8245	-0.1027	-0.0924	2.0686	0.338864
161	0.8247	-0.1030	-0.0923	2.0687	0.338861
162	0.8249	-0.1032	-0.0922	2.0689	0.338857
163	0.8252	-0.1034	-0.0921	2.0690	0.338854
164	0.8254	-0.1036	-0.0920	2.0691	0.338851
165	0.8256	-0.1038	-0.0919	2.0692	0.338849
166	0.8258	-0.1040	-0.0919	2.0693	0.338846
167	0.8260	-0.1042	-0.0918	2.0694	0.338844
168	0.8262	-0.1044	-0.0917	2.0695	0.338841
169	0.8264	-0.1046	-0.0916	2.0696	0.338839
170	0.8266	-0.1048	-0.0915	2.0697	0.338837
171	0.8268	-0.1050	-0.0915	2.0698	0.338835
172	0.8270	-0.1052	-0.0914	2.0699	0.338833
173	0.8272	-0.1053	-0.0913	2.0699	0.338831
174	0.8273	-0.1055	-0.0913	2.0700	0.338829
175	0.8275	-0.1057	-0.0912	2.0701	0.338828
176	0.8276	-0.1059	-0.0911	2.0702	0.338826

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177     0.8278    -0.1060    -0.0911     2.0702         0.338825
178     0.8280    -0.1062    -0.0910     2.0703         0.338823
179     0.8281    -0.1063    -0.0909     2.0704         0.338822
180     0.8283    -0.1065    -0.0909     2.0704         0.338820
181     0.8284    -0.1066    -0.0908     2.0705         0.338819
182     0.8285    -0.1068    -0.0908     2.0706         0.338818
183     0.8287    -0.1069    -0.0907     2.0706         0.338817
184     0.8288    -0.1071    -0.0906     2.0707         0.338816
185     0.8289    -0.1072    -0.0906     2.0707         0.338815
186     0.8291    -0.1073    -0.0905     2.0708         0.338814
187     0.8292    -0.1075    -0.0905     2.0708         0.338813
188     0.8293    -0.1076    -0.0904     2.0709         0.338812
189     0.8295    -0.1077    -0.0904     2.0709         0.338811
190     0.8296    -0.1078    -0.0903     2.0709         0.338810
191     0.8297    -0.1080    -0.0903     2.0710         0.338809
192     0.8298    -0.1081    -0.0902     2.0710         0.338809
193     0.8299    -0.1082    -0.0902     2.0711         0.338808
194     0.8300    -0.1083    -0.0901     2.0711         0.338807
195     0.8301    -0.1084    -0.0901     2.0711         0.338807
196     0.8303    -0.1085    -0.0901     2.0711         0.338806
197     0.8304    -0.1086    -0.0900     2.0712         0.338806
198     0.8304    -0.1087    -0.0900     2.0712         0.338805
199     0.8305    -0.1088    -0.0899     2.0712         0.338805
200     0.8306    -0.1088    -0.0899     2.0713         0.338804
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724	0.8346	-0.1129	-0.0881	2.0719	0.338794
725	0.8346	-0.1129	-0.0881	2.0719	0.338794
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731	0.8346	-0.1129	-0.0881	2.0719	0.338794
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736	0.8346	-0.1129	-0.0881	2.0719	0.338794

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754	0.8346	-0.1130	-0.0881	2.0719	0.338794
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980	0.8346	-0.1129	-0.0881	2.0719	0.338794
981	0.8346	-0.1129	-0.0881	2.0719	0.338794
982	0.8346	-0.1129	-0.0881	2.0719	0.338794
983	0.8346	-0.1129	-0.0881	2.0719	0.338794
984	0.8346	-0.1129	-0.0881	2.0719	0.338794
985	0.8345	-0.1129	-0.0881	2.0719	0.338794
986	0.8346	-0.1129	-0.0881	2.0719	0.338794
987	0.8346	-0.1129	-0.0881	2.0719	0.338794
988	0.8346	-0.1129	-0.0881	2.0719	0.338794
989	0.8346	-0.1129	-0.0881	2.0719	0.338794
990	0.8346	-0.1129	-0.0881	2.0719	0.338794
991	0.8346	-0.1129	-0.0881	2.0719	0.338794
992	0.8346	-0.1129	-0.0881	2.0719	0.338794
993	0.8346	-0.1129	-0.0881	2.0719	0.338794
994	0.8346	-0.1129	-0.0881	2.0719	0.338794
995	0.8346	-0.1129	-0.0881	2.0720	0.338794
996	0.8346	-0.1129	-0.0881	2.0720	0.338794
997	0.8346	-0.1129	-0.0881	2.0720	0.338794
998	0.8346	-0.1129	-0.0881	2.0720	0.338794
999	0.8346	-0.1129	-0.0881	2.0720	0.338794
1000	0.8346	-0.1129	-0.0881	2.0720	0.338794

In [17]:

```
print("Final iteration (1000) values for Mini-Batch SGD:\n")
for frac in batch_fractions:
    w_final, b_final, J_hist = results[frac]
    print(f"Mini-Batch {int(frac*100)}%:")
    print(f"w1 = {w_final[0,0]:.6f}, w2 = {w_final[1,0]:.6f}, w3 = {w_final[2,0]:.6
    print(f"J(w,b) = {J_hist[-1]:.6f}\n")
```

```
Final iteration (1000) values for Mini-Batch SGD:

Mini-Batch 10%:
w1 = 0.834560, w2 = -0.112831, w3 = -0.088143, b = 2.071929
J(w,b) = 0.338794

Mini-Batch 20%:
w1 = 0.834591, w2 = -0.112914, w3 = -0.088148, b = 2.071943
J(w,b) = 0.338794

Mini-Batch 25%:
w1 = 0.834575, w2 = -0.112920, w3 = -0.088142, b = 2.071954
J(w,b) = 0.338794
```

In [18]:

```
# Store the final weights and bias for Mini Batch GD with 10%, 20% and 25% batch si

final_params_mini_batch = {}
for frac in batch_fractions:
    w_final, b_final, J_hist = results[frac]
    final_params_mini_batch[frac] = (w_final, b_final)
```

In [19]:

```
import plotly.graph_objects as go
import numpy as np

step = 20
iterations = np.arange(0, len(J_hist), step)
J_BGD = np.array(J_hist)[iterations]

fig = go.Figure()
fig.add_trace(go.Scatter(
    x=iterations+1,
    y=J_BGD,
    mode='lines+markers',
    name="BGD",
    text=[f"Iteration {i+1}: J={v:.6f}" for i,v in zip(iterations, J_BGD)],
    hoverinfo='text'
))

fig.update_layout(
    title="Convergence of Batch Gradient Descent (BGD)",
    xaxis_title="Iteration",
    yaxis_title="Objective Function J(w,b)",
    template="plotly_white",
    hovermode="closest"
)
fig.show()
```

In [20]:

```
J_mini10 = np.array(results[0.1][2])[iterations]

fig = go.Figure()
fig.add_trace(go.Scatter(
    x=iterations+1,
    y=J_mini10,
    mode='lines+markers',
```

```
    name="Mini-Batch 10%",
    text=[f"Iteration {i+1}: J={v:.6f}" for i,v in zip(iterations, J_mini10)],
    hoverinfo='text'
))

fig.update_layout(
    title="Convergence of Mini-Batch SGD (10% batch)",
    xaxis_title="Iteration",
    yaxis_title="Objective Function J(w,b)",
    template="plotly_white",
    hovermode="closest"
)
fig.show()
```

In [21]:
```
J_mini20 = np.array(results[0.2][2])[iterations]

fig = go.Figure()
fig.add_trace(go.Scatter(
    x=iterations+1,
    y=J_mini20,
    mode='lines+markers',
    name="Mini-Batch 20%",
    text=[f"Iteration {i+1}: J={v:.6f}" for i,v in zip(iterations, J_mini20)],
    hoverinfo='text'
))

fig.update_layout(
    title="Convergence of Mini-Batch SGD (20% batch)",
    xaxis_title="Iteration",
    yaxis_title="Objective Function J(w,b)",
    template="plotly_white",
    hovermode="closest"
)
fig.show()
```

In [22]:
```python
J_mini25 = np.array(results[0.25][2])[iterations]

fig = go.Figure()
fig.add_trace(go.Scatter(
    x=iterations+1,
    y=J_mini25,
    mode='lines+markers',
    name="Mini-Batch 25%",
    text=[f"Iteration {i+1}: J={v:.6f}" for i,v in zip(iterations, J_mini25)],
    hoverinfo='text'
))

fig.update_layout(
    title="Convergence of Mini-Batch SGD (25% batch)",
    xaxis_title="Iteration",
    yaxis_title="Objective Function J(w,b)",
    template="plotly_white",
    hovermode="closest"
)
fig.show()
```

Task - 5 : Compute training and MSE, With R-Score for Each Algorithm in table and Graph

The MSE and R-Score Can be Calculated as Follows :

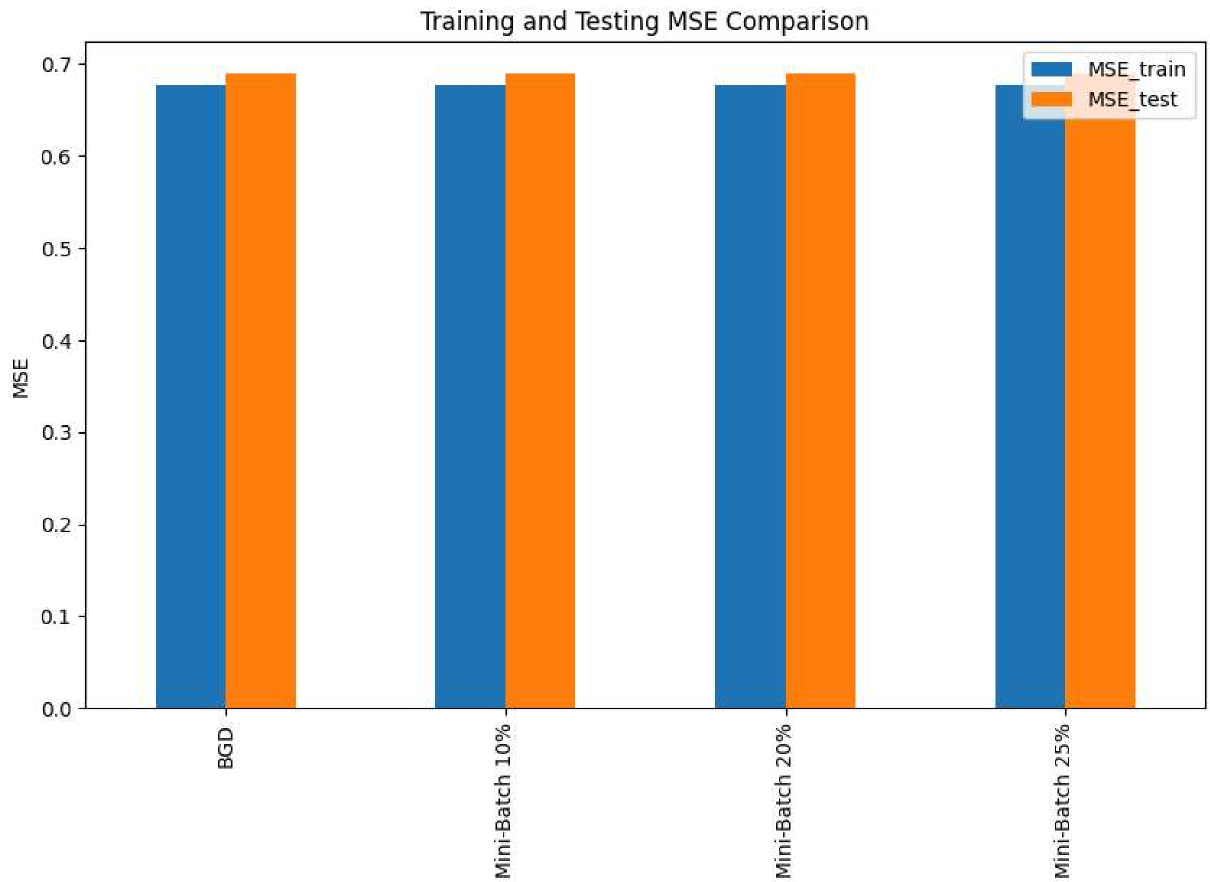
$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

In [23]:
```python
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score

# Define evaluate_model here so this cell can run independently
def evaluate_model(X, y, w, b):
    """
    Evaluate linear model predictions y_pred = X @ w + b
    Returns (mse, r2)
    """
    y_pred = X @ w + b
    mse = mean_squared_error(y, y_pred)
    r2 = r2_score(y, y_pred)
    return mse, r2
```

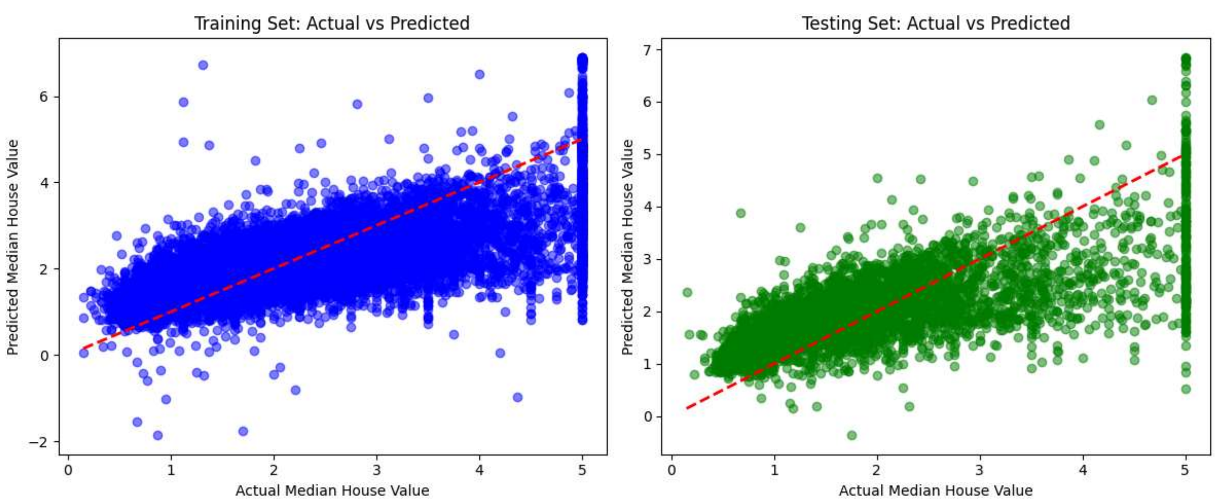
```python
# --- Store final parameters for all algorithms ---
final_params = {
    'BGD': (w_final, b_final)
}

# Add Mini-Batch SGD
for frac in batch_fractions:
    w_mini, b_mini = final_params_mini_batch[frac]
    final_params[f'Mini-Batch {int(frac*100)}%'] = (w_mini, b_mini)

# --- Evaluate all models ---
results_eval = {}
for algo, (w, b) in final_params.items():
    mse_train, r2_train = evaluate_model(X_train, y_train, w, b)
    mse_test, r2_test = evaluate_model(X_test, y_test, w, b)
    results_eval[algo] = {
        'MSE_train': mse_train,
        'R2_train': r2_train,
        'MSE_test': mse_test,
        'R2_test': r2_test
    }

# --- Convert results to DataFrame for table display ---
df_results = pd.DataFrame(results_eval).T
print(df_results)

# --- Plot MSE comparison ---
df_results[['MSE_train', 'MSE_test']].plot(kind='bar', figsize=(10,6))
plt.title("Training and Testing MSE Comparison")
plt.ylabel("MSE")
plt.show()

# --- Plot R2 comparison ---
df_results[['R2_train', 'R2_test']].plot(kind='bar', figsize=(10,6))
plt.title("Training and Testing R² Comparison")
plt.ylabel("R² Score")
plt.show()
```

```
                MSE_train  R2_train  MSE_test   R2_test
BGD              0.677587  0.493119  0.689429  0.473883
Mini-Batch 10%   0.677587  0.493119  0.689430  0.473881
Mini-Batch 20%   0.677587  0.493119  0.689430  0.473882
Mini-Batch 25%   0.677587  0.493119  0.689429  0.473883
```



Predicitions :

In [24]:
```
import matplotlib.pyplot as plt
import numpy as np

# Predictions for train and test
y_train_pred = X_train @ w_final + b_final
y_test_pred  = X_test  @ w_final + b_final

# Plot
plt.figure(figsize=(12,5))

# Training set
plt.subplot(1,2,1)
plt.scatter(y_train, y_train_pred, alpha=0.5, color='blue')
plt.plot([y_train.min(), y_train.max()], [y_train.min(), y_train.max()], 'r--', lw=
plt.title("Training Set: Actual vs Predicted")
plt.xlabel("Actual Median House Value")
plt.ylabel("Predicted Median House Value")

# Testing set
plt.subplot(1,2,2)
plt.scatter(y_test, y_test_pred, alpha=0.5, color='green')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.title("Testing Set: Actual vs Predicted")
plt.xlabel("Actual Median House Value")
plt.ylabel("Predicted Median House Value")

plt.tight_layout()
plt.show()
```



Results From Above :

1. We can Explain only the 50% Variance

2. We can Predict only the half of the values

3. Model is very simple as we are taking only the mostly correlated features

4. In General, House Price prediction is Complex in Nature

What if we use all Features ?

In [25]:
```
data = fetch_california_housing()
X = pd.DataFrame(data.data, columns=data.feature_names)
y = data.target.reshape(-1,1)

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)


X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, ran


N, d = X_train.shape
w0 = np.zeros((d,1))
b0 = 0
eta = 0.01
max_iter = 1000
epsilon = 1e-6


def batch_gradient_descent(X, y, w_init, b_init, eta, max_iter, epsilon):
    N, d = X.shape
    w = w_init.copy()
    b = b_init
    J_history = []

    for iter_num in range(max_iter):
        y_hat = np.dot(X, w) + b
        e = y_hat - y
        dw = (1/N) * np.dot(X.T, e)
        db = (1/N) * np.sum(e)
        w -= eta * dw
        b -= eta * db
        J = (1/(2*N)) * np.sum(e**2)
        J_history.append(J)
        if np.linalg.norm(dw) < epsilon and abs(db) < epsilon:
            break
    return w, b, J_history

w_bgd, b_bgd, J_bgd = batch_gradient_descent(X_train, y_train, w0, b0, eta, max_ite



def mini_batch_sgd(X, y, w_init, b_init, eta=0.01, max_iter=1000, batch_frac=0.1, e
    N, d = X.shape
    batch_size = max(1, int(N * batch_frac))
    w = w_init.copy()
    b = b_init
    J_history = []

    for iter_num in range(max_iter):
        indices = np.arange(N)
        np.random.shuffle(indices)
```

```
        X_shuffled = X[indices]
        y_shuffled = y[indices]

        for start in range(0, N, batch_size):
            end = start + batch_size
            X_batch = X_shuffled[start:end]
            y_batch = y_shuffled[start:end]

            y_hat = np.dot(X_batch, w) + b
            e = y_hat - y_batch
            dw = (1/batch_size) * np.dot(X_batch.T, e)
            db = (1/batch_size) * np.sum(e)
            w -= eta * dw
            b -= eta * db

        y_hat_full = np.dot(X, w) + b
        e_full = y_hat_full - y
        J = (1/(2*N)) * np.sum(e_full**2)
        J_history.append(J)

        if np.linalg.norm(dw) < epsilon and abs(db) < epsilon:
            break

    return w, b, J_history

batch_fractions = [0.1, 0.2, 0.25]
results_mini = {}

for frac in batch_fractions:
    w_m, b_m, J_m = mini_batch_sgd(X_train, y_train, w0, b0, eta, max_iter, batch_f
    results_mini[frac] = (w_m, b_m, J_m)

def evaluate_model(X, y, w, b):
    y_pred = np.dot(X, w) + b
    mse = mean_squared_error(y, y_pred)
    r2 = r2_score(y, y_pred)
    return mse, r2


results_table = []

# BGD
mse_train, r2_train = evaluate_model(X_train, y_train, w_bgd, b_bgd)
mse_test, r2_test = evaluate_model(X_test, y_test, w_bgd, b_bgd)
results_table.append(['BGD', mse_train, r2_train, mse_test, r2_test])

# Mini-Batch
for frac in batch_fractions:
    w_m, b_m, _ = results_mini[frac]
    mse_train, r2_train = evaluate_model(X_train, y_train, w_m, b_m)
    mse_test, r2_test = evaluate_model(X_test, y_test, w_m, b_m)
    results_table.append([f'Mini-Batch {int(frac*100)}%', mse_train, r2_train, mse_

df_results = pd.DataFrame(results_table, columns=['Algorithm', 'MSE_train', 'R2_tra
print(df_results)
```

```
         Algorithm  MSE_train  R2_train  MSE_test   R2_test
0              BGD   0.548713  0.589526  0.567340  0.567051
1  Mini-Batch 10%   0.517934  0.612551  0.555995  0.575709
2  Mini-Batch 20%   0.518062  0.612455  0.555780  0.575873
3  Mini-Batch 25%   0.518382  0.612215  0.555069  0.576416
```

Previously R2 Score was around 0.47 and now it is 0.57 after adding all features

Why still only 57, Math is good and also all Features got Selected ?

How to Improve Model Performance

1. **Feature Engineering**
   Create new features or combinations of existing ones to capture more patterns.
2. **Outlier Handling**
   Identify and remove or adjust extreme values in the dataset that may distort the model.
3. **Non-linear Models**
   Linear regression is limited. Consider using more complex models.
4. **Regularization Tuning**
   L1 (Lasso) or L2 (Ridge) penalties prevent overfitting. Tuning the regularization strength can improve performance.
5. **Feature Selection / Dimensionality Reduction**
   Remove highly correlated features or use PCA to reduce dimensions while keeping important information.

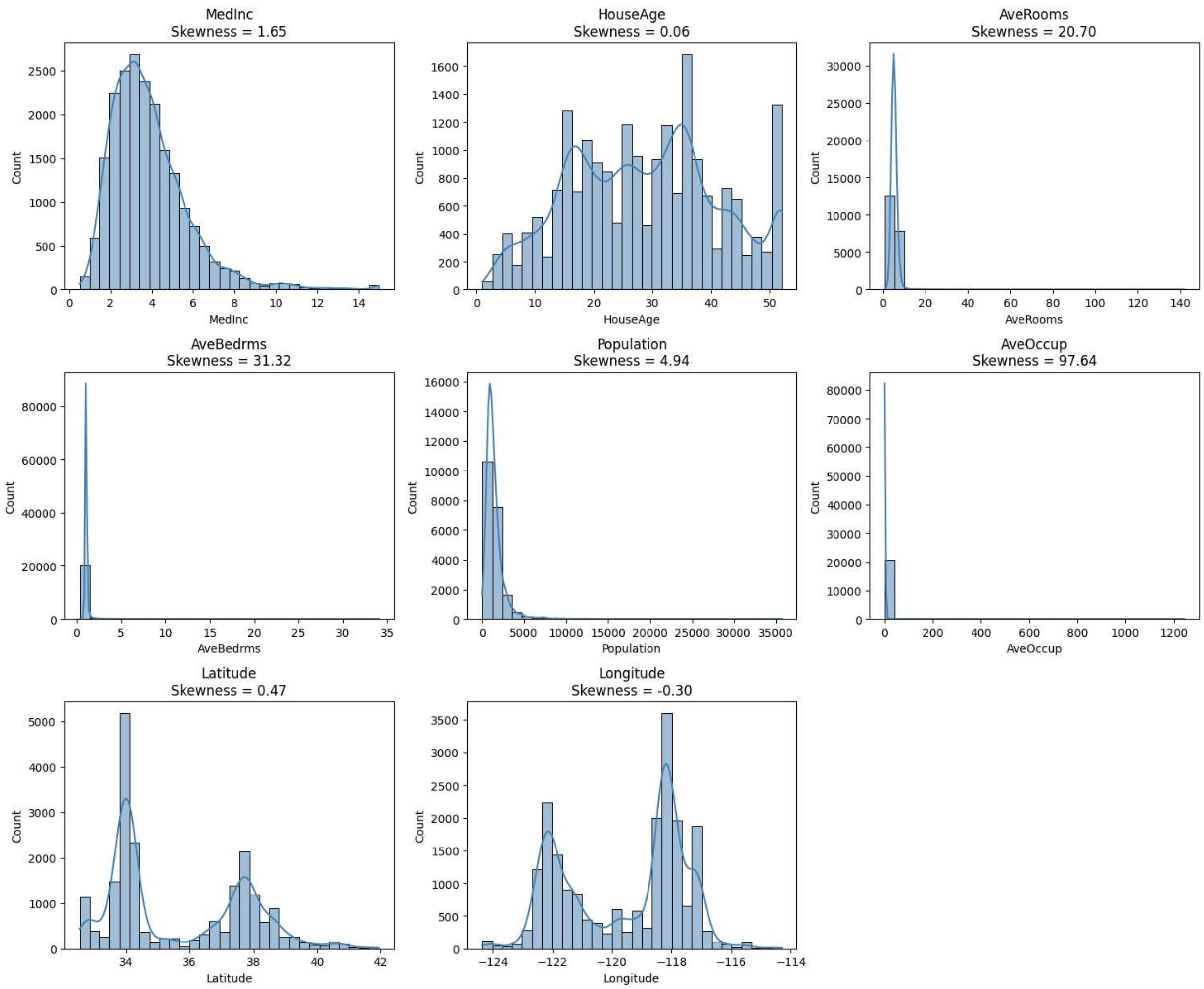
Let's Check the Skewness of the Variables

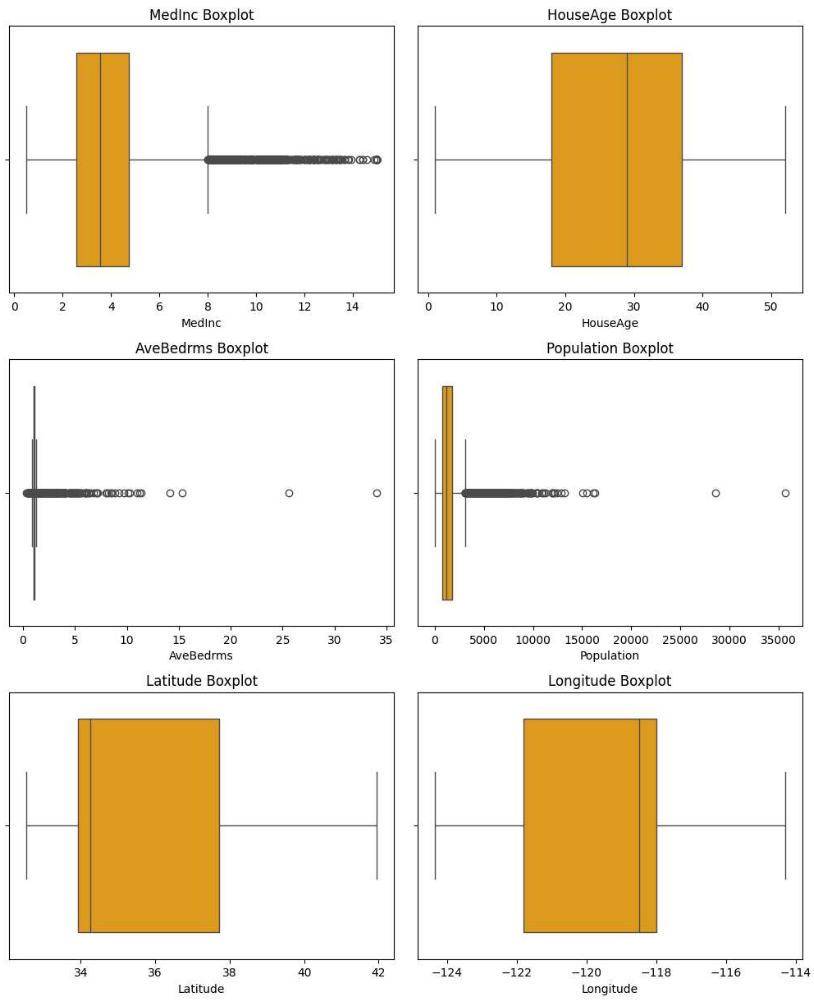
$$\mathrm{Skew}(x) = \frac{E[(x-\mu)^3]}{\sigma^3}$$

In [26]:
```python
data = fetch_california_housing()
df = pd.DataFrame(data.data, columns=data.feature_names)
df['median_house_value'] = data.target

features = df.columns.drop('median_house_value')

# Compute skewness
skewness = df[features].skew().sort_values(ascending=False)
```

```python
print("Feature Skewness:\n", skewness)

# Visualize distributions
plt.figure(figsize=(15, 20))
for i, col in enumerate(features, 1):
    plt.subplot(5, 3, i)   # adjust grid depending on number of features
    sns.histplot(df[col], kde=True, color='steelblue', bins=30)
    plt.title(f"{col}\nSkewness = {df[col].skew():.2f}")
plt.tight_layout()
plt.show()

# Optional: Boxplots for Outlier Visualization
plt.figure(figsize=(15, 20))
for i, col in enumerate(features, 1):
    plt.subplot(5, 3, i)
    sns.boxplot(x=df[col], color='orange')
    plt.title(f"{col} Boxplot")
plt.tight_layout()
plt.show()
```

```
Feature Skewness:
 AveOccup      97.639561
AveBedrms     31.316956
AveRooms      20.697869
Population     4.935858
MedInc         1.646657
Latitude       0.465953
HouseAge       0.060331
Longitude     -0.297801
dtype: float64
```


MedInc
Skewness = 1.65
HouseAge
Skewness = 0.06
AveRooms
Skewness = 20.70
AveBedrms
Skewness = 31.32
Population
Skewness = 4.94
AveOccup
Skewness = 97.64
Latitude
Skewness = 0.47
Longitude
Skewness = -0.30
Count



Problems with Skewed Data

When the feature distribution is **highly skewed**, it violates the assumptions of many statistical and machine learning models (especially linear regression).
This leads to unstable training, biased predictions, and poor generalization.

---

1. Mean ≠ Median ≠ Mode → Bias in Linear Models

- In skewed distributions, mean, median, and mode differ significantly.
- Linear Regression minimizes the **Mean Squared Error (MSE)**
- Thus, **outliers dominate** the model — pulling the regression line toward the tail and biasing predictions.

→ **Effect:** Poor fit for majority of samples.

---

2. Heteroscedasticity (Non-Constant Variance)

- Skewed data often causes **non-constant variance of residuals**:

- Violates one of the core linear model assumptions.
- Leads to **biased standard errors**, invalid p-values, and unreliable confidence intervals.

→ **Effect:** Statistical inference becomes incorrect; model is not robust.

---

3. Gradient Descent Becomes Unstable

- Gradient updates depend on the magnitude of features
- Causes **slower convergence**, **unstable training**, or **suboptimal minima**.

→ **Effect:** Optimization oscillates or converges poorly.

Solutions to Handle Skewness

Problem	Practical Fix	Explanation
Bias due to outliers	**Apply log / sqrt / Box-Cox transform**	Compresses large values and stabilizes mean–variance relationship
Heteroscedasticity	**Variance-stabilizing transforms (log/yeo-johnson)**	Makes residuals more homoscedastic (constant variance)
Gradient instability	**Feature scaling (StandardScaler / MinMaxScaler)**	Normalizes feature magnitudes for smooth gradient flow
Strong outliers	**Winsorization / Capping / Clipping**	Limit extreme tail values
Very complex skew	**Use non-linear models (Tree-based, SVR, NN)**	Models nonlinear relationships that linear models can't capture

---

Common Transformations for Skewed Data

Skew Type	Shape	Typical Fixes
-	**Right-skewed**	Long right tail	Log Transform
		Square Root
		Cube Root
		Reciprocal
| Left-skewed	Long left tail	Square / Cube
		Exponential
| Symmetric but Non-normal	Moderate deviations	Box–Cox Transform
| Zeros or Negatives Present	Right-skewed with zeros	Yeo–Johnson Transform

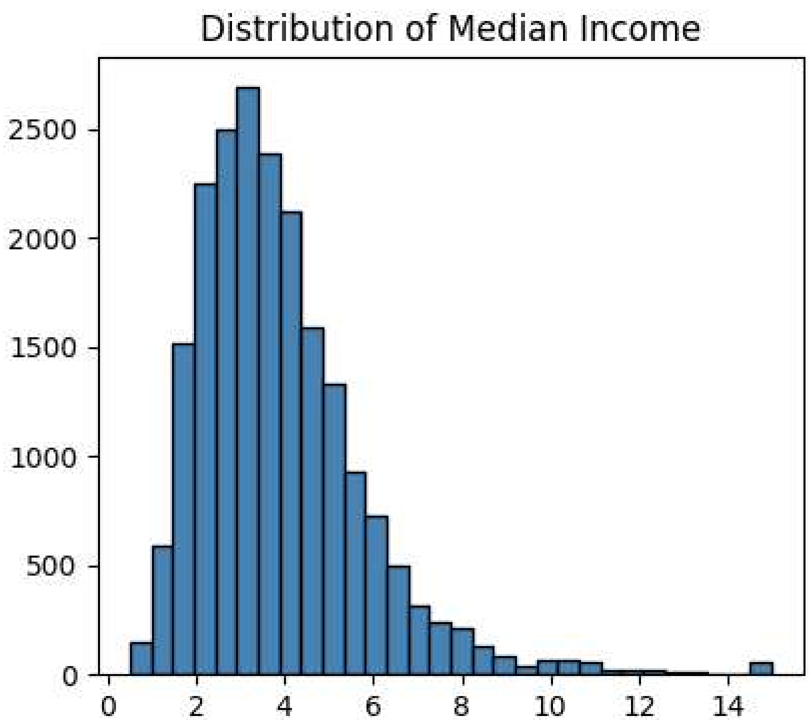
Let's Study Each feature Seperately

1. Median Income :

Histogram --- Used for Understanding Distribution and Outliers

In [27]:
```
data = fetch_california_housing()
df = pd.DataFrame(data.data, columns=data.feature_names)
df['Medinc'] = data.data[:, 0]  # Median Income


plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
plt.hist(df['Medinc'], bins=30, color='steelblue', edgecolor='black')
plt.title("Distribution of Median Income")
```

Out[27]: Text(0.5, 1.0, 'Distribution of Median Income')



In [28]:
```
df.describe()
```

Out[28]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070655
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386050
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692308
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429741
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818116
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282261
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333333

In [29]:

```
#Count no of zeros or negatives & Skewness in Median Income
zero_count = (df['Medinc'] == 0).sum()
negative_count = (df['Medinc'] < 0).sum()
print(f"Number of zeros in Median Income: {zero_count}")
print(f"Number of negative values in Median Income: {negative_count}")

df['Medinc'].skew()
```

```
Number of zeros in Median Income: 0
Number of negative values in Median Income: 0
```

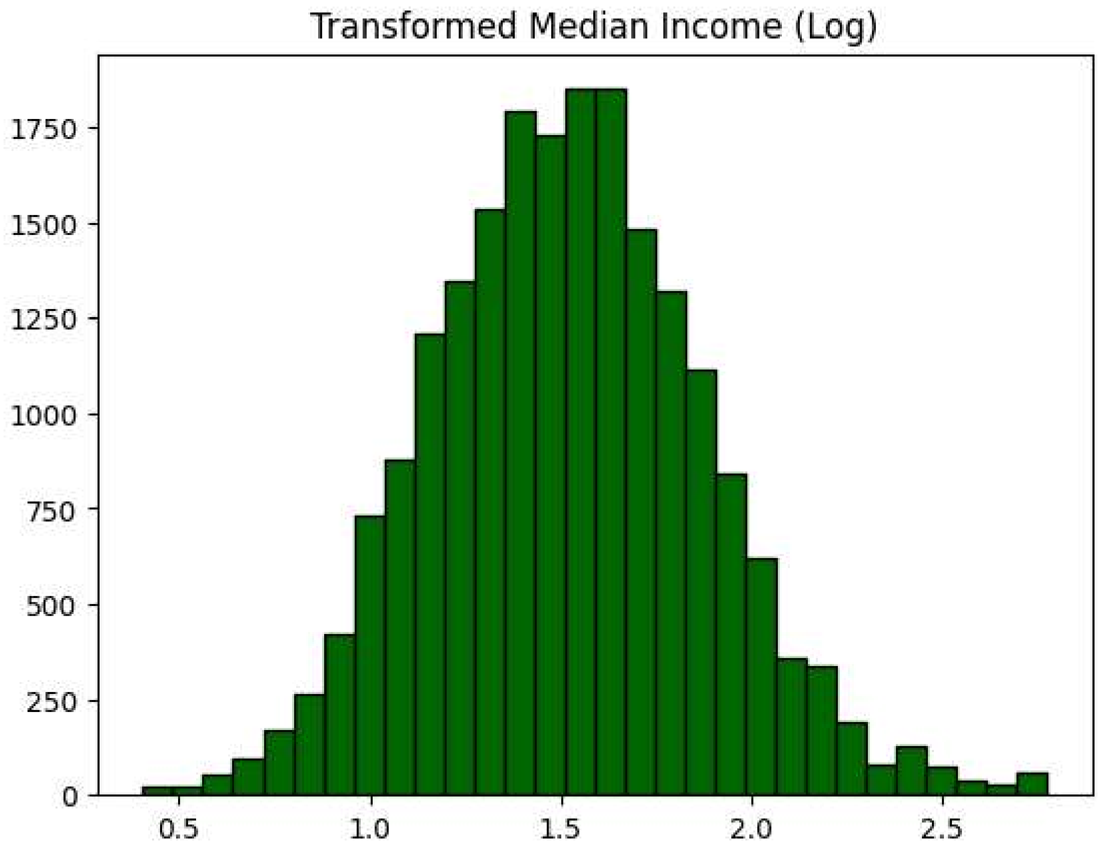
Out[29]: np.float64(1.6466567021344465)

If Skewness > 1 ---> Apply Log Transformation

If 0.5 < Skewness < 1 ---> Apply Sqrt transformation

In [30]:

```
# Applying the Log transformation

df['Medinc_log'] = np.log1p(df['Medinc'])

plt.hist(df['Medinc_log'], bins=30, color='darkgreen', edgecolor='black')
plt.title("Transformed Median Income (Log)")
plt.show()

print("Original skew:", df['Medinc'].skew())
print("Transformed skew:", df['Medinc_log'].skew())
```




```
Original skew: 1.6466567021344465
Transformed skew: 0.22608313067130548
```

In [31]:
```
df.describe()
```

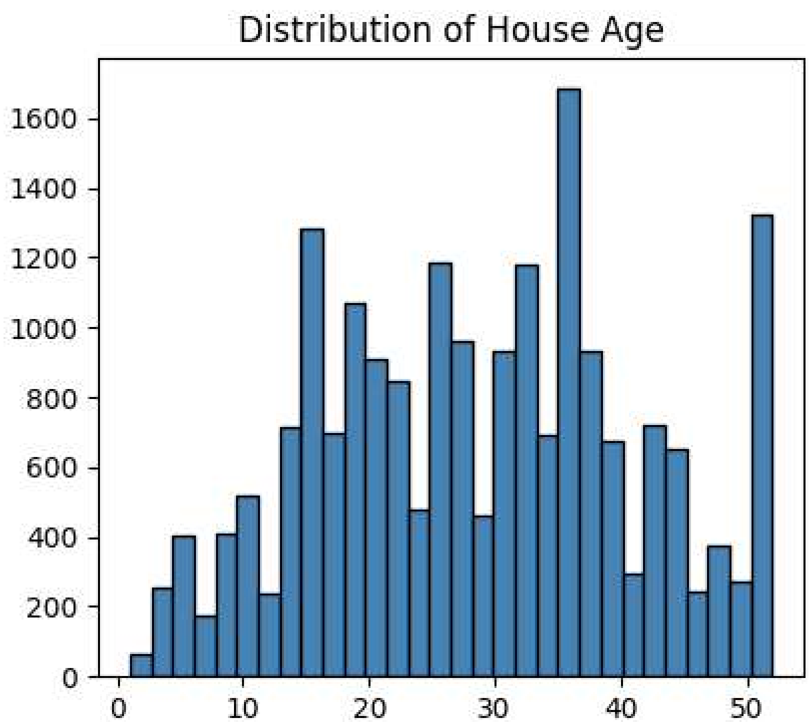
Out[31]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070655
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386050
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692308
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429741
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818116
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282261
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333333

2. Housing Median Age

In [32]:
```
plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
plt.hist(df['HouseAge'], bins=30, color='steelblue', edgecolor='black')
plt.title("Distribution of House Age")
```

Out[32]: Text(0.5, 1.0, 'Distribution of House Age')



In [33]:
```
#Count no of zeros or negatives & Skewness in HouseAge
zero_count = (df['HouseAge'] == 0).sum()
negative_count = (df['HouseAge'] < 0).sum()
print(f"Number of zeros in House Age: {zero_count}")
print(f"Number of negative values in House Age: {negative_count}")
df['HouseAge'].skew()
```

```
Number of zeros in House Age: 0
Number of negative values in House Age: 0
```

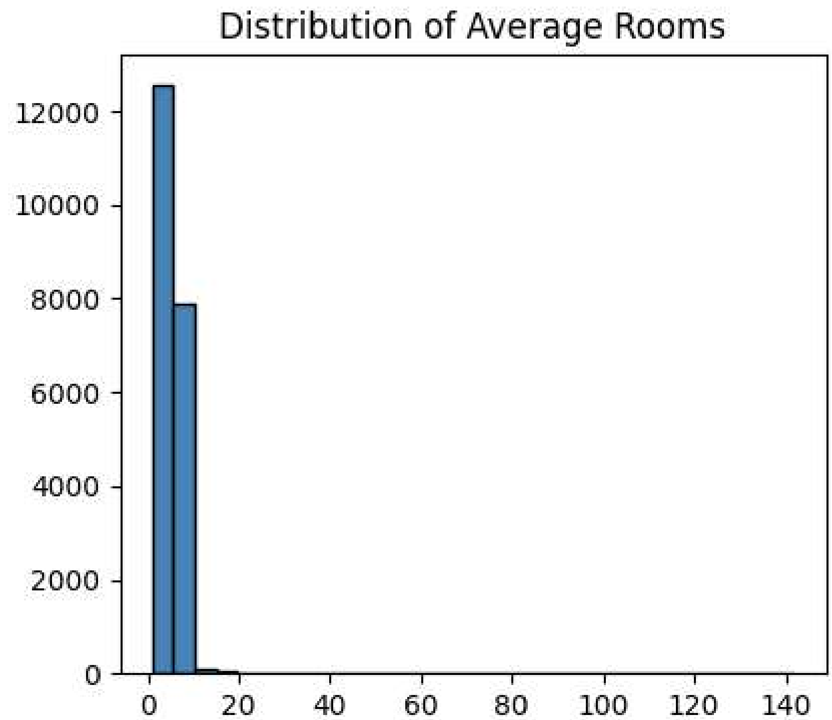
Out[33]: np.float64(0.060330637599136865)

No Transformation Needed For House median Age

3. Average No of Rooms

In [34]:
```
plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
plt.hist(df['AveRooms'], bins=30, color='steelblue', edgecolor='black')
plt.title("Distribution of Average Rooms")
```

Out[34]: Text(0.5, 1.0, 'Distribution of Average Rooms')



In [35]:
```
#Count no of zeros or negatives & Skewness in AveRooms

zero_count = (df['AveRooms'] == 0).sum()
negative_count = (df['AveRooms'] < 0).sum()
print(f"Number of zeros in Average Rooms: {zero_count}")
print(f"Number of negative values in Average Rooms: {negative_count}")
df['AveRooms'].skew()
```

```
Number of zeros in Average Rooms: 0
Number of negative values in Average Rooms: 0
```

Out[35]: np.float64(20.697868956710646)

In [36]:
```
#Finding the Summary Statistics for Average No of Rooms
summary = df['AveRooms'].describe().T
print(summary)
```

```
count    20640.000000
mean         5.429000
std          2.474173
min          0.846154
25%          4.440716
50%          5.229129
75%          6.052381
max        141.909091
Name: AveRooms, dtype: float64
```

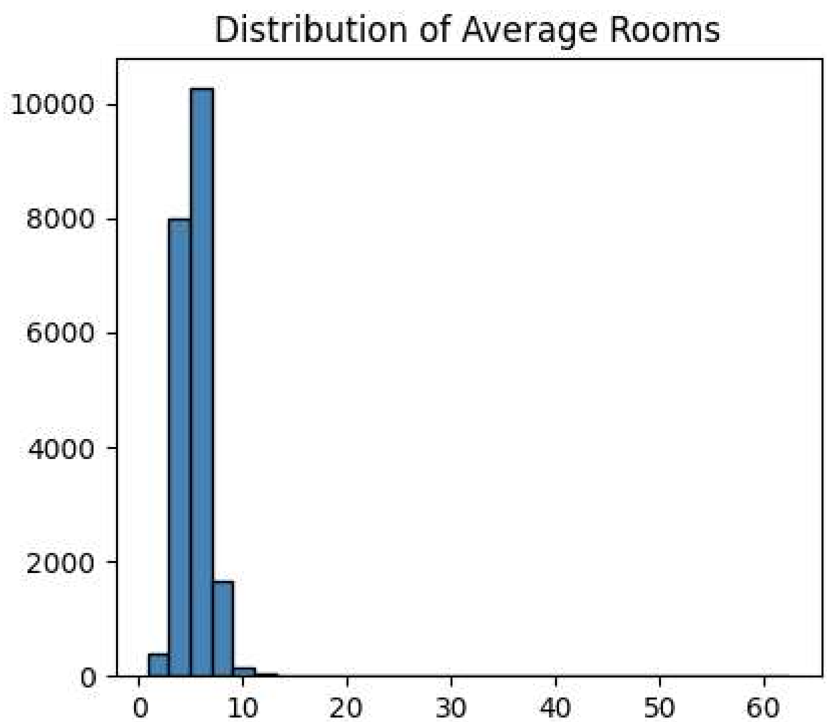
In [37]:
```
# Replacing the outliers with Mode
mode_value = df['AveRooms'].mode()[0]
df.loc[df['AveRooms'] > 65, 'AveRooms'] = mode_value
```

In [38]:
```
summary = df['AveRooms'].describe().T
print(summary)
```

```
count    20640.000000
mean         5.416188
std          2.106209
min          0.846154
25%          4.440716
50%          5.228714
75%          6.052096
max         62.422222
Name: AveRooms, dtype: float64
```

In [39]:
```
plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
plt.hist(df['AveRooms'], bins=30, color='steelblue', edgecolor='black')
plt.title("Distribution of Average Rooms")
```

Out[39]: `Text(0.5, 1.0, 'Distribution of Average Rooms')`

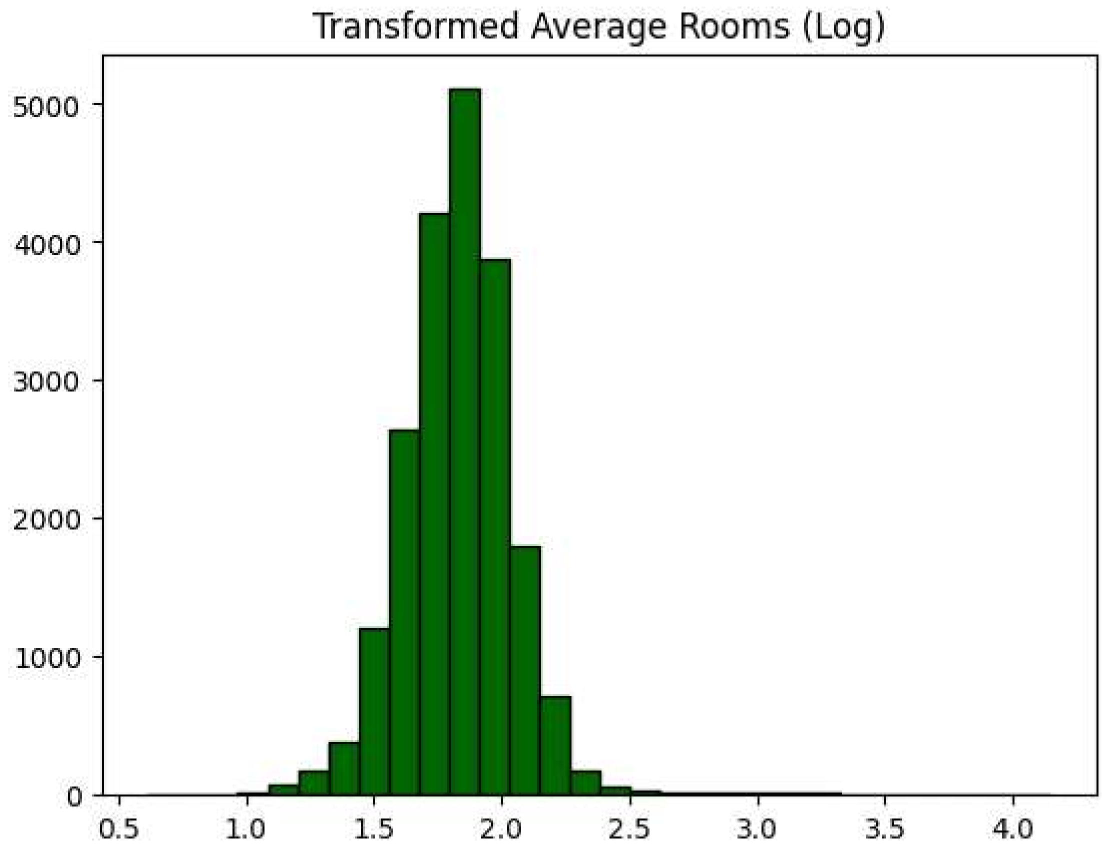


In [40]:
```
#Skewness after outlier treatment
df['AveRooms'].skew()
```

Out[40]: `np.float64(9.735904326903938)`

Log Transformation :

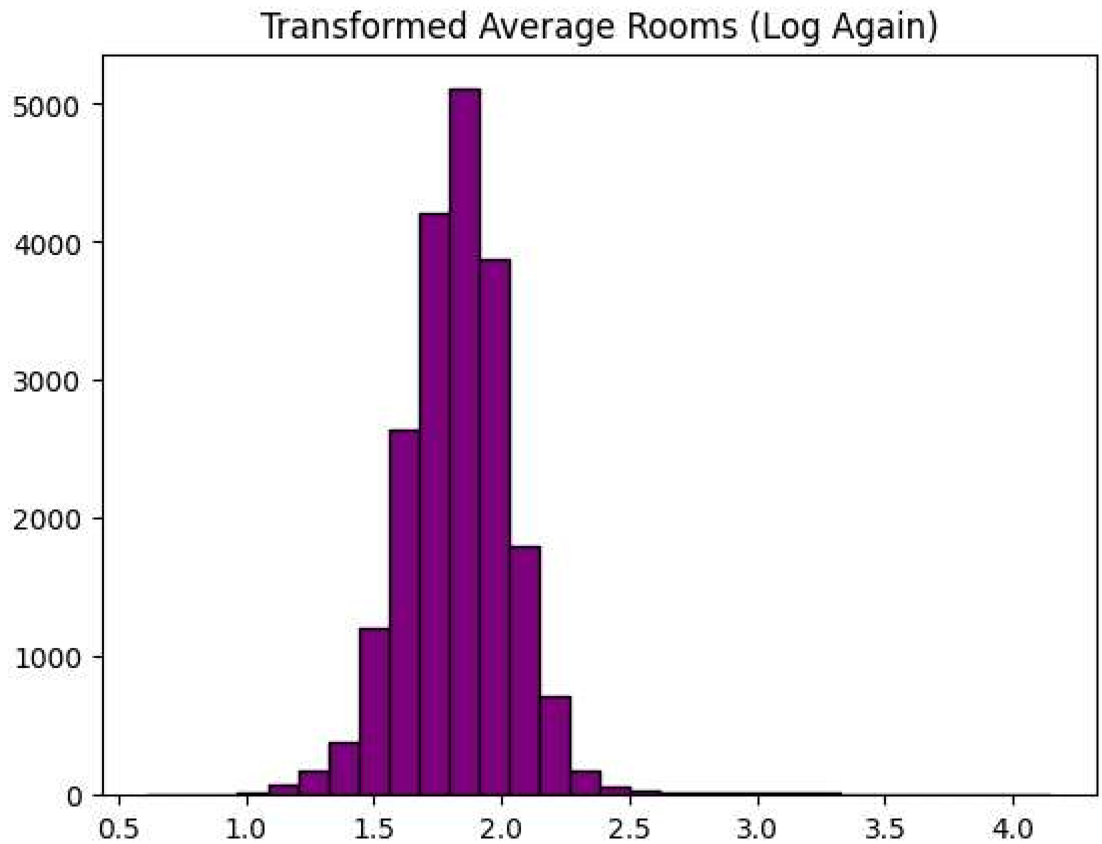
In [41]:
```
# Applying Log Transformation
df['AveRooms_log'] = np.log1p(df['AveRooms'])
plt.hist(df['AveRooms_log'], bins=30, color='darkgreen', edgecolor='black')
plt.title("Transformed Average Rooms (Log)")
plt.show()
print("Transformed skew:", df['AveRooms_log'].skew())
```




```
Transformed skew: 1.1941128112163357
```

In [42]:

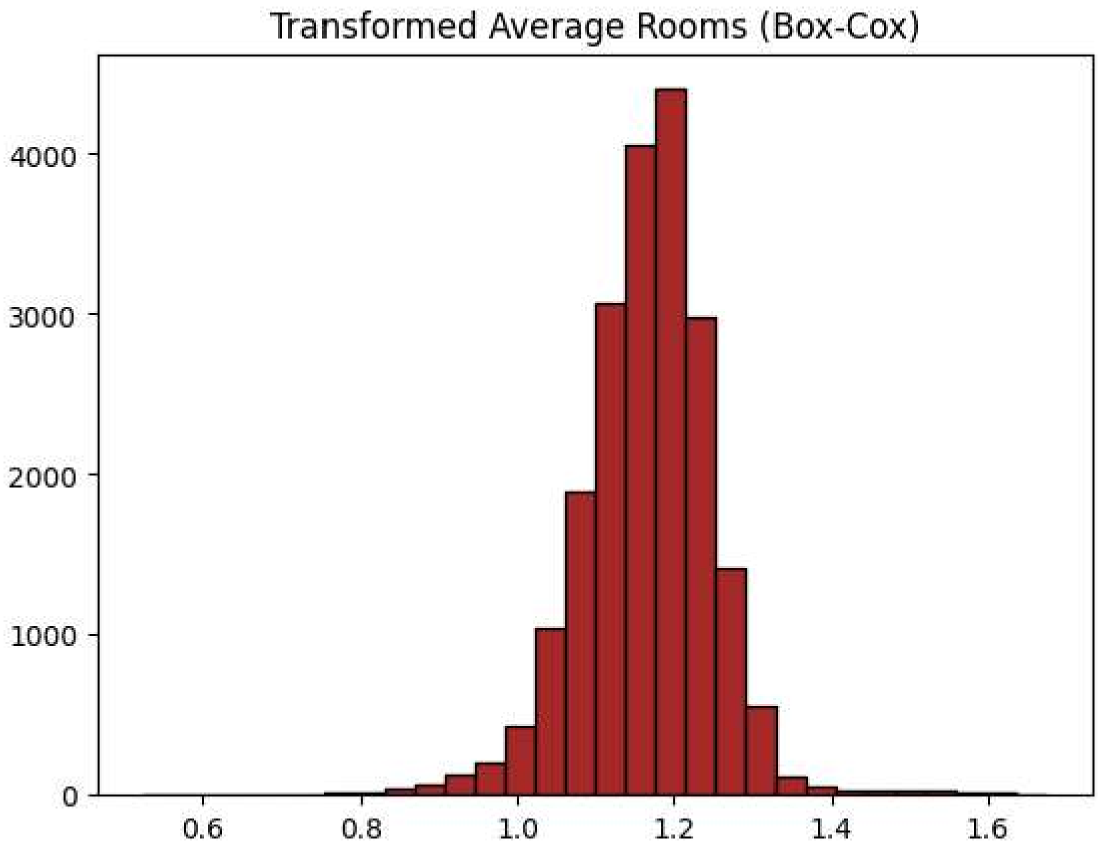
```python
# Again applying the Log transformation for better results

df['AveRooms_log2'] = np.log1p(df['AveRooms'])
plt.hist(df['AveRooms_log2'], bins=30, color='purple', edgecolor='black')
plt.title("Transformed Average Rooms (Log Again)")
plt.show()
print("Transformed skew again:", df['AveRooms_log2'].skew())
```




```
Transformed skew again: 1.1941128112163357
```

So We apply box-cox transformation to the main column

In [43]:
```
# Applying the box-cox transformation for the AveRooms feature Directly

from scipy import stats
df['AveRooms_boxcox'], fitted_lambda = stats.boxcox(df['AveRooms'] + 1)  # Adding 1
plt.hist(df['AveRooms_boxcox'], bins=30, color='brown', edgecolor='black')
plt.title("Transformed Average Rooms (Box-Cox)")
plt.show()
print("Box-Cox transformed skew:", df['AveRooms_boxcox'].skew())
```




```
Box-Cox transformed skew: -0.1553014747638362
```

In [44]:
```python
df.describe()
```

Out[44]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	3.870671	28.639486	5.416188	1.096675	1425.476744	3.070655
std	1.899822	12.585558	2.106209	0.473911	1132.462122	10.386050
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692308
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429741
50%	3.534800	29.000000	5.228714	1.048780	1166.000000	2.818116
75%	4.743250	37.000000	6.052096	1.099526	1725.000000	3.282261
max	15.000100	52.000000	62.422222	34.066667	35682.000000	1243.333333

In [45]:
```python
# Dropping the original columns after transformation
df = df.drop(columns=['Medinc', 'AveRooms', 'MedInc'])

# Also drop intermediate transformed columns to keep only final ones
df = df.drop(columns=['AveRooms_log', 'AveRooms_log2'])

df.describe()
```

Out[45]:

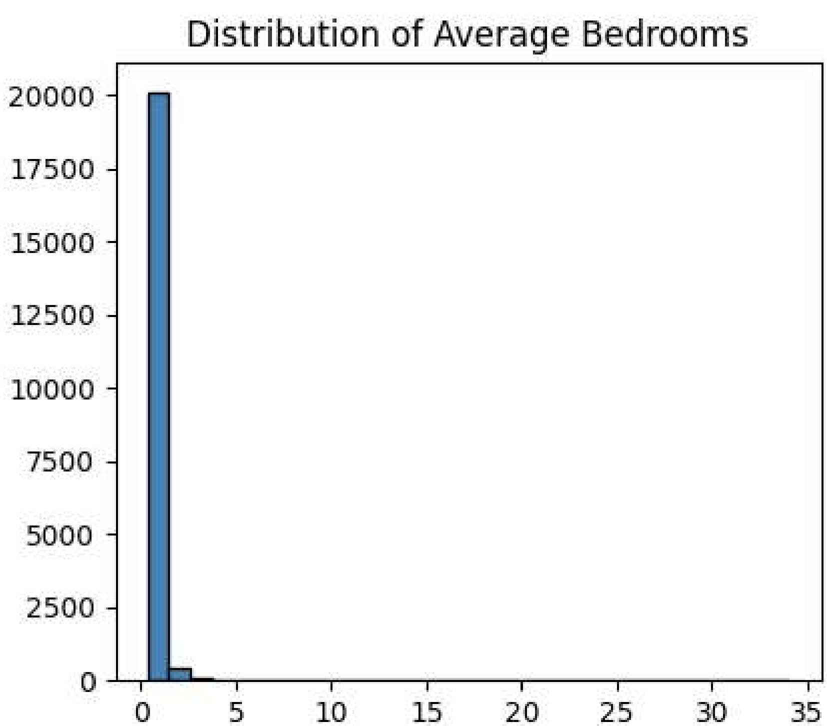
	HouseAge	AveBedrms	Population	AveOccup	Latitude	Longitude
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	28.639486	1.096675	1425.476744	3.070655	35.631861	-119.569704
std	12.585558	0.473911	1132.462122	10.386050	2.135952	2.003532
min	1.000000	0.333333	3.000000	0.692308	32.540000	-124.350000
25%	18.000000	1.006079	787.000000	2.429741	33.930000	-121.800000
50%	29.000000	1.048780	1166.000000	2.818116	34.260000	-118.490000
75%	37.000000	1.099526	1725.000000	3.282261	37.710000	-118.010000
max	52.000000	34.066667	35682.000000	1243.333333	41.950000	-114.310000

4. Average Bedrooms :

In [46]:

```
plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
plt.hist(df['AveBedrms'], bins=30, color='steelblue', edgecolor='black')
plt.title("Distribution of Average Bedrooms")
```

Out[46]: `Text(0.5, 1.0, 'Distribution of Average Bedrooms')`



In [47]:

```
#Count no of zeros or negatives & Skewness in bedrooms
zero_count = (df['AveBedrms'] == 0).sum()
negative_count = (df['AveBedrms'] < 0).sum()
print(f"Number of zeros in Average Bedrooms: {zero_count}")
```

```
print(f"Number of negative values in Average Bedrooms: {negative_count}")
df['AveBedrms'].skew()
```

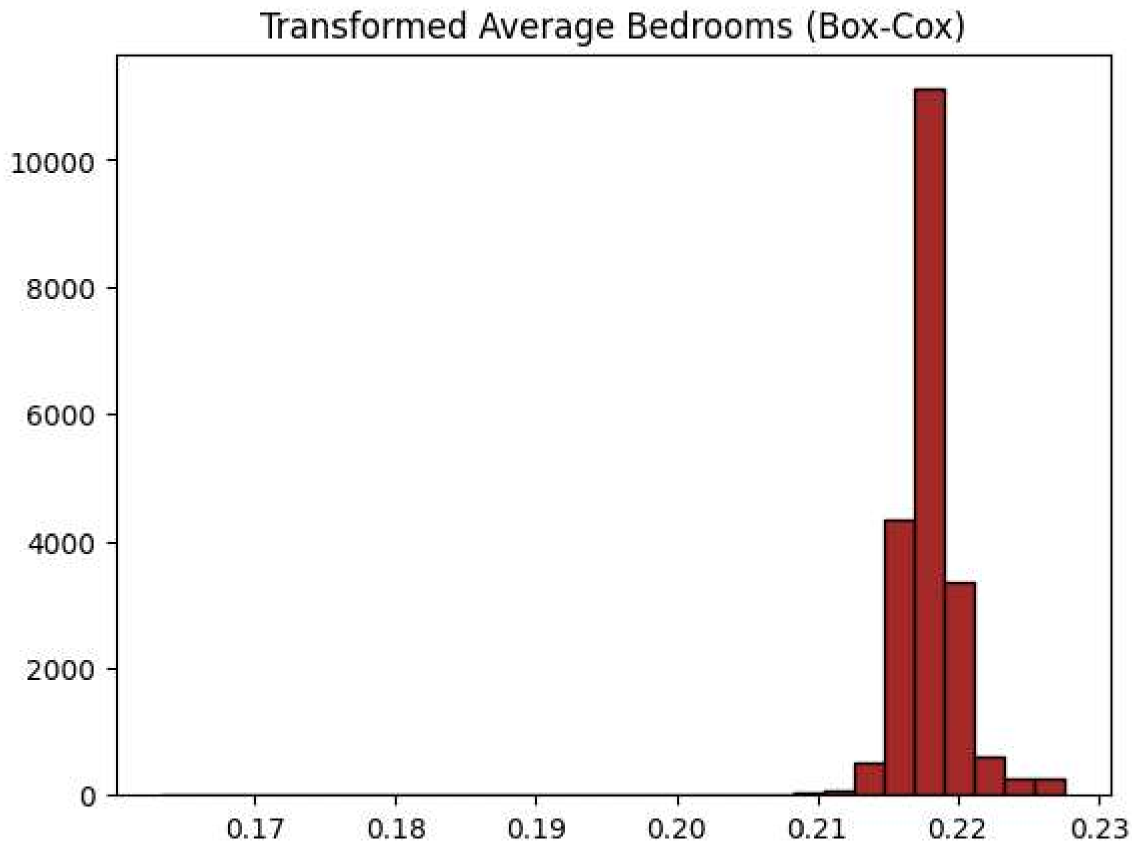
```
Number of zeros in Average Bedrooms: 0
Number of negative values in Average Bedrooms: 0
```

Out[47]: np.float64(31.316956246782663)

In [48]:
```
#Applying Log Transformation

df['AveBedrms_log'] = np.log1p(df['AveBedrms'])
plt.hist(df['AveBedrms_log'], bins=30, color='darkgreen', edgecolor='black')
plt.title("Transformed Average Bedrooms (Log)")
plt.show()
print("Transformed skew:", df['AveBedrms_log'].skew())
```


```
Transformed skew: 8.988786093389573
```

In [49]:
```
# So applying Box-Cox Transformation for AveBedrms feature Directly and dropping th

from scipy import stats
df['AveBedrms_boxcox'], fitted_lambda = stats.boxcox(df['AveBedrms'] + 1)  # Adding
plt.hist(df['AveBedrms_boxcox'], bins=30, color='brown', edgecolor='black')
plt.title("Transformed Average Bedrooms (Box-Cox)")
plt.show()
print("Box-Cox transformed skew:", df['AveBedrms_boxcox'].skew())
df = df.drop(columns=['AveBedrms', 'AveBedrms_log'])
```




```
Box-Cox transformed skew: -1.446666850345764
```

In [50]:
```
df.describe()
```

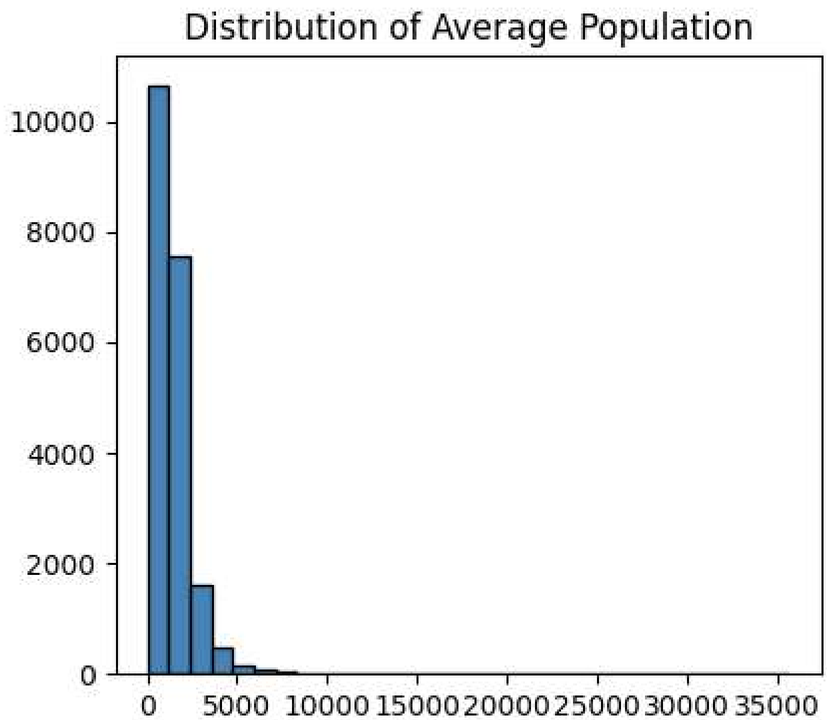
Out[50]:

	HouseAge	Population	AveOccup	Latitude	Longitude	Medinc_log
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	28.639486	1425.476744	3.070655	35.631861	-119.569704	1.516995
std	12.585558	1132.462122	10.386050	2.135952	2.003532	0.358677
min	1.000000	3.000000	0.692308	32.540000	-124.350000	0.405398
25%	18.000000	787.000000	2.429741	33.930000	-121.800000	1.270715
50%	29.000000	1166.000000	2.818116	34.260000	-118.490000	1.511781
75%	37.000000	1725.000000	3.282261	37.710000	-118.010000	1.748025
max	52.000000	35682.000000	1243.333333	41.950000	-114.310000	2.772595

5. Population :

In [51]:
```
plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
plt.hist(df['Population'], bins=30, color='steelblue', edgecolor='black')
plt.title("Distribution of Average Population")
```

Out[51]: Text(0.5, 1.0, 'Distribution of Average Population')

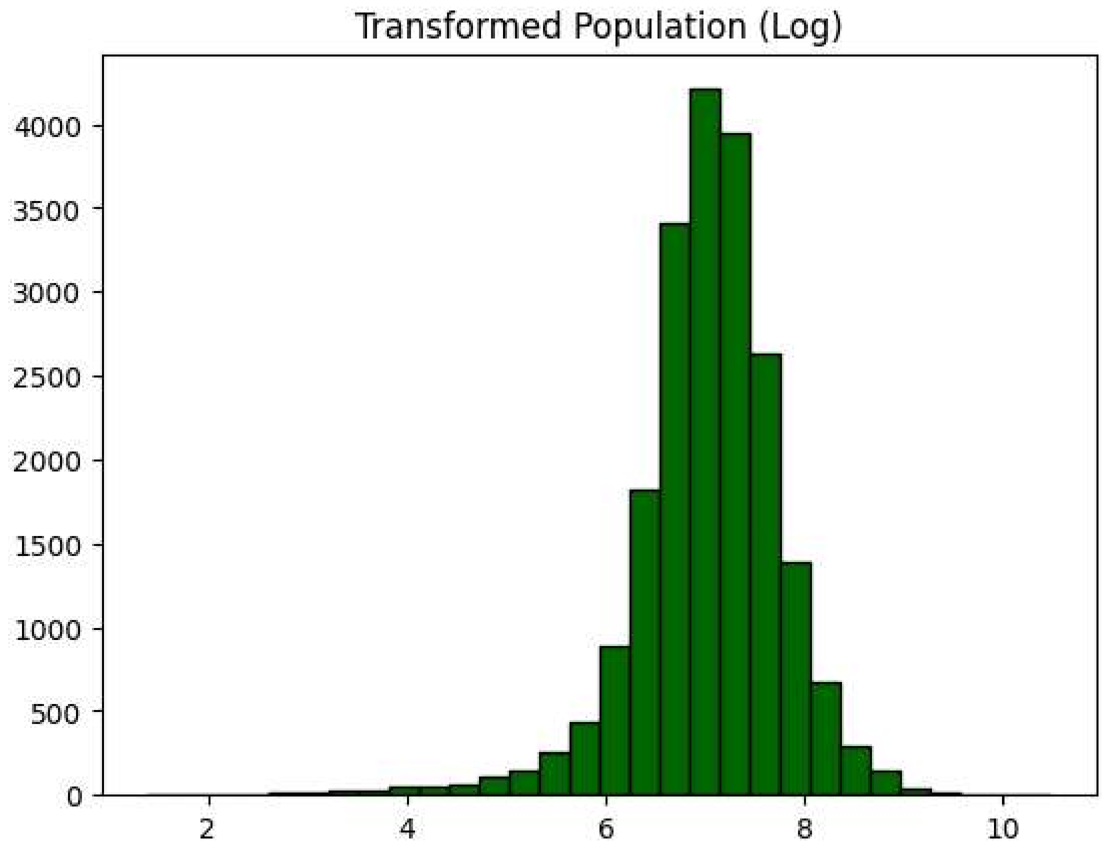


In [52]:
```
# Count no of zeros or negatives & Skewness in Population
zero_count = (df['Population'] == 0).sum()
negative_count = (df['Population'] < 0).sum()
print(f"Number of zeros in Population: {zero_count}")
print(f"Number of negative values in Population: {negative_count}")
df['Population'].skew()
```

```
Number of zeros in Population: 0
Number of negative values in Population: 0
```

Out[52]: np.float64(4.93585822672712)

In [53]:
```
# Applying Log Transformation

df['Population_log'] = np.log1p(df['Population'])
plt.hist(df['Population_log'], bins=30, color='darkgreen', edgecolor='black')
plt.title("Transformed Population (Log)")
plt.show()
print("Transformed skew:", df['Population_log'].skew())
```




```
Transformed skew: -1.0440866961519721
```

In [54]:
```
#Dropping the original Population column after transformation

df = df.drop(columns=['Population'])
df.describe()
```

Out[54]:

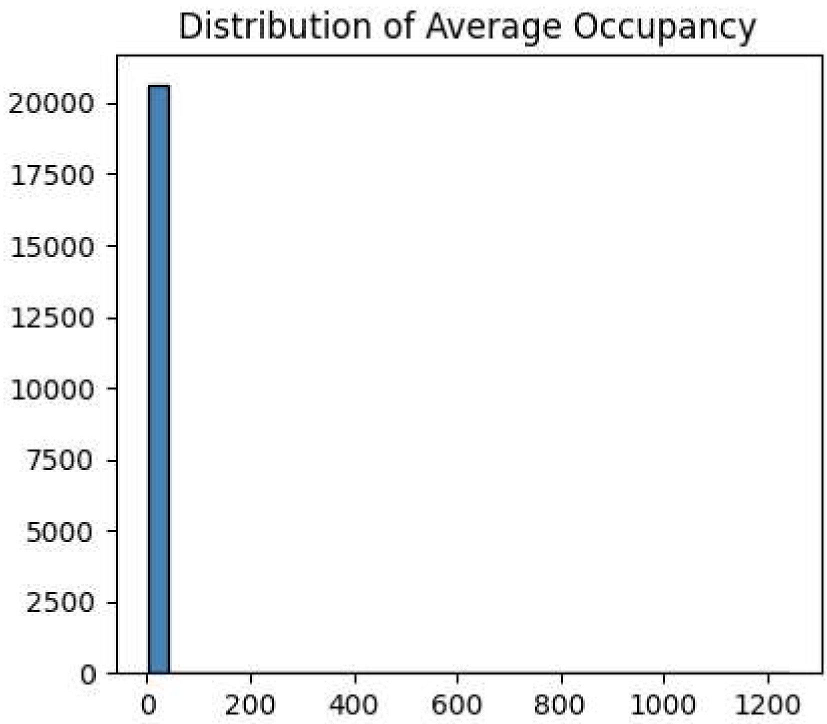
	HouseAge	AveOccup	Latitude	Longitude	Medinc_log	AveRooms_b
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.0
mean	28.639486	3.070655	35.631861	-119.569704	1.516995	1.1
std	12.585558	10.386050	2.135952	2.003532	0.358677	0.0
min	1.000000	0.692308	32.540000	-124.350000	0.405398	0.5
25%	18.000000	2.429741	33.930000	-121.800000	1.270715	1.1
50%	29.000000	2.818116	34.260000	-118.490000	1.511781	1.1
75%	37.000000	3.282261	37.710000	-118.010000	1.748025	1.2
max	52.000000	1243.333333	41.950000	-114.310000	2.772595	1.6

6. AveOccup :

In [55]:
```
# Histogram of AveOccupation
plt.figure(figsize=(10,4))
```

```
plt.subplot(1,2,1)
plt.hist(df['AveOccup'], bins=30, color='steelblue', edgecolor='black')
plt.title("Distribution of Average Occupancy")
```

Out[55]: Text(0.5, 1.0, 'Distribution of Average Occupancy')

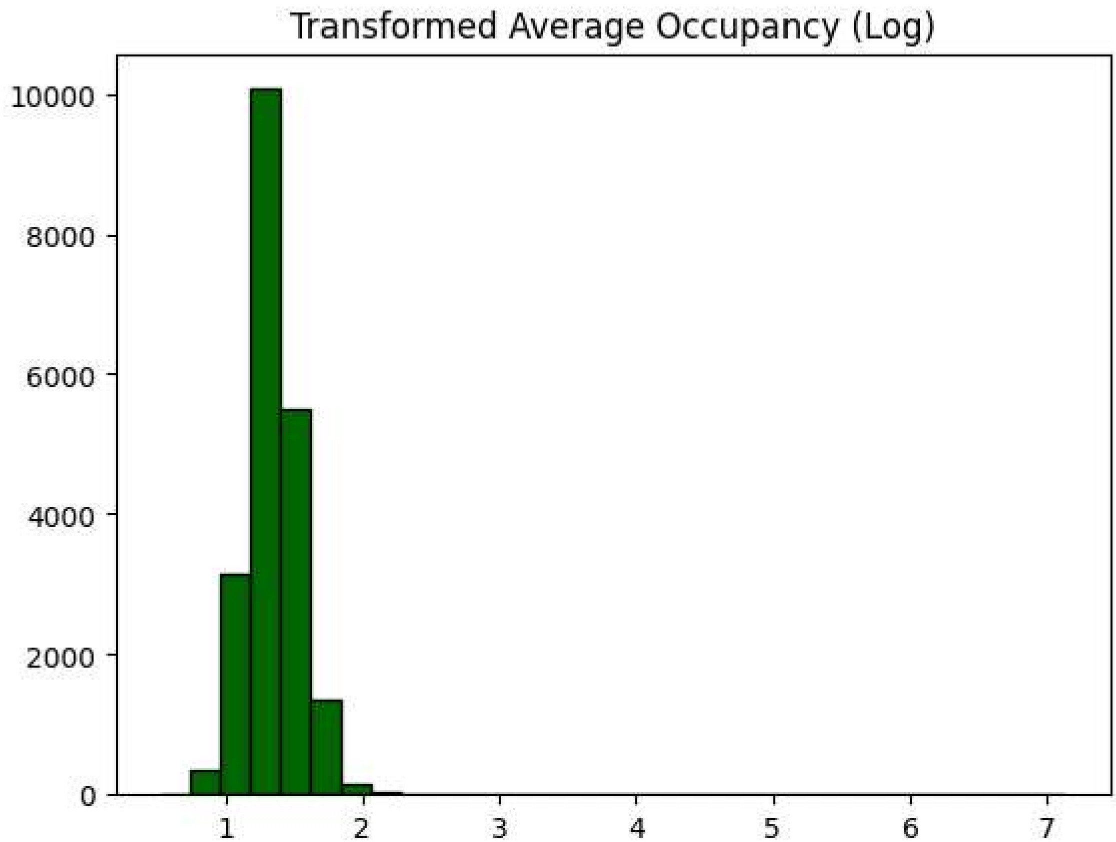


In [56]:
```
# Count no of zeros or negatives & Skewness in AveOccup
zero_count = (df['AveOccup'] == 0).sum()
negative_count = (df['AveOccup'] < 0).sum()
print(f"Number of zeros in Average Occupancy: {zero_count}")
print(f"Number of negative values in Average Occupancy: {negative_count}")
df['AveOccup'].skew()
```

```
Number of zeros in Average Occupancy: 0
Number of negative values in Average Occupancy: 0
```

Out[56]: np.float64(97.63956096369479)

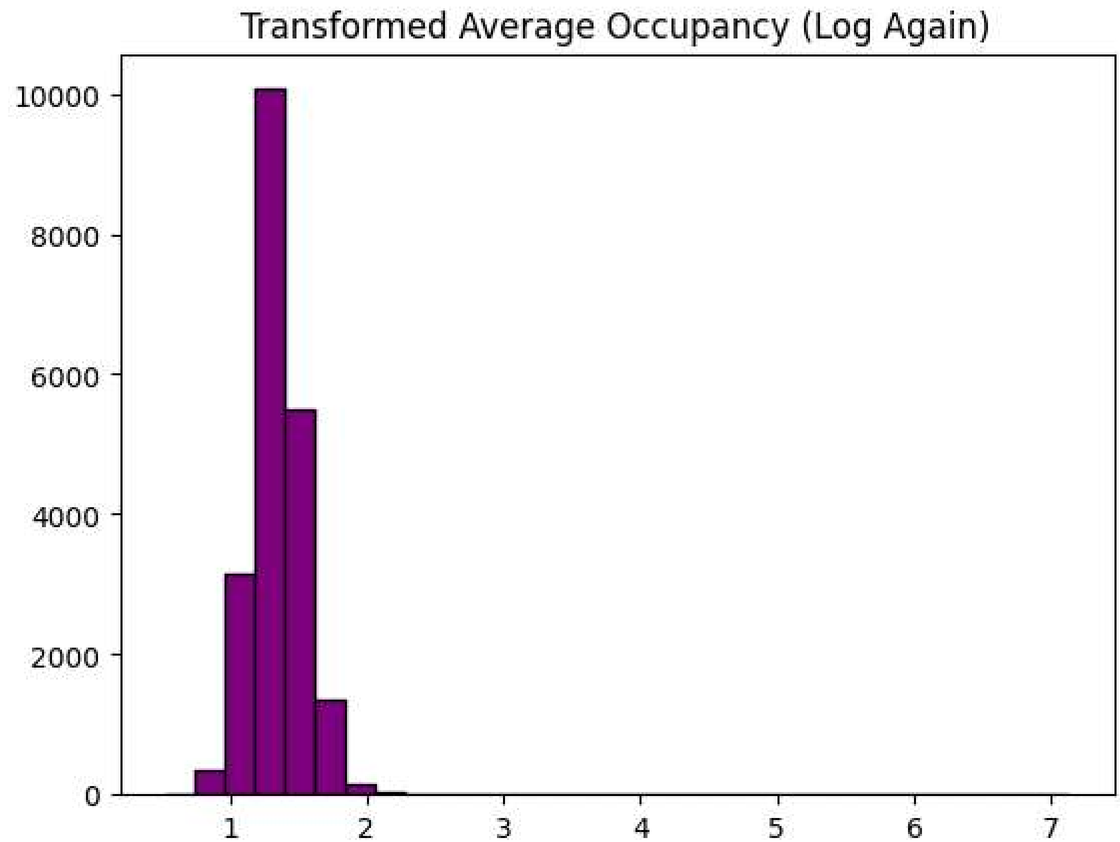
In [57]:
```
# Applying Log Transformation for AveOccup

df['AveOccup_log'] = np.log1p(df['AveOccup'])
plt.hist(df['AveOccup_log'], bins=30, color='darkgreen', edgecolor='black')
plt.title("Transformed Average Occupancy (Log)")
plt.show()
print("Transformed skew:", df['AveOccup_log'].skew())
```




```
Transformed skew: 3.8796788829093227
```

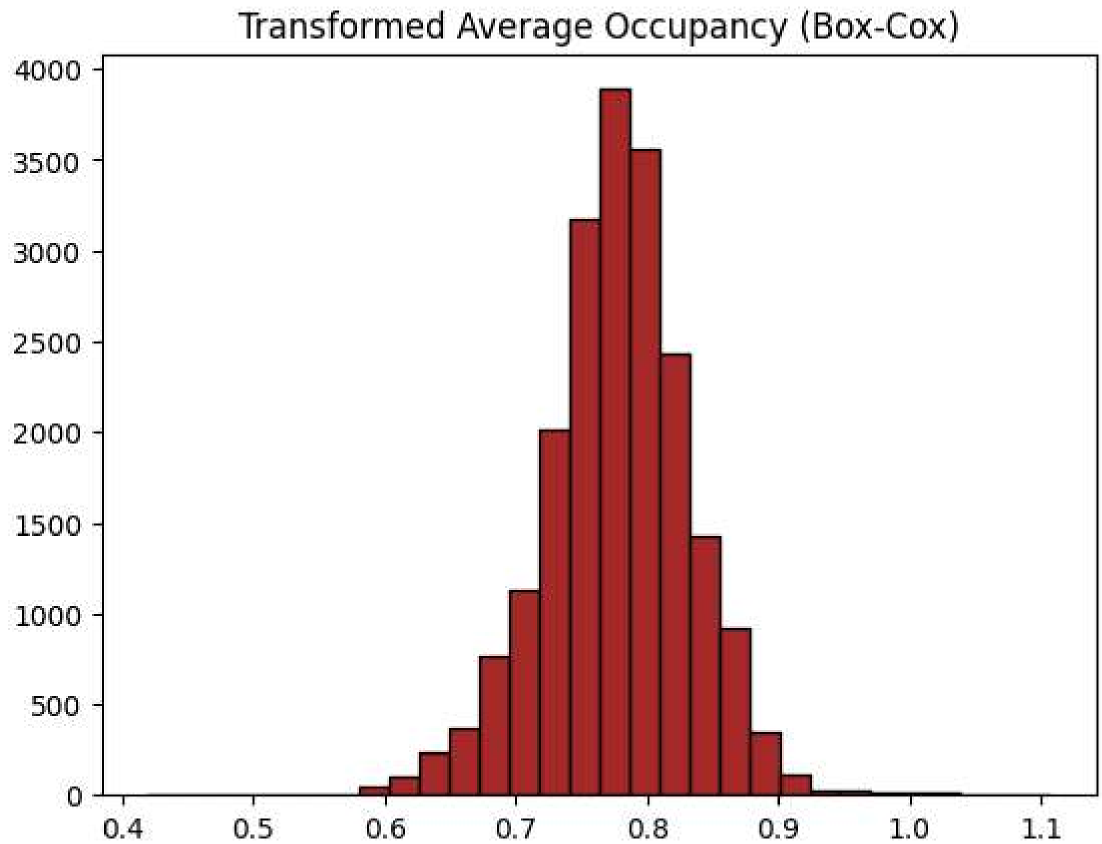
In [58]:

```
# Applying Log Transformation again for better results
df['AveOccup_log2'] = np.log1p(df['AveOccup'])
plt.hist(df['AveOccup_log2'], bins=30, color='purple', edgecolor='black')
plt.title("Transformed Average Occupancy (Log Again)")
plt.show()
print("Transformed skew again:", df['AveOccup_log2'].skew())
```




```
Transformed skew again: 3.8796788829093227
```

In [59]:
```
# So Applying Box-Cox Transformation for AveOccup feature Directly and dropping the

from scipy import stats
df['AveOccup_boxcox'], fitted_lambda = stats.boxcox(df['AveOccup'] + 1)  # Adding 1
plt.hist(df['AveOccup_boxcox'], bins=30, color='brown', edgecolor='black')
plt.title("Transformed Average Occupancy (Box-Cox)")
plt.show()
print("Box-Cox transformed skew:", df['AveOccup_boxcox'].skew())
```




```
Box-Cox transformed skew: -0.10688770830394234
```

In [60]:
```
# Dropping the original AveOccup column and log transformed columns after Box-Cox t

df = df.drop(columns=['AveOccup', 'AveOccup_log', 'AveOccup_log2'])
df.describe()
```

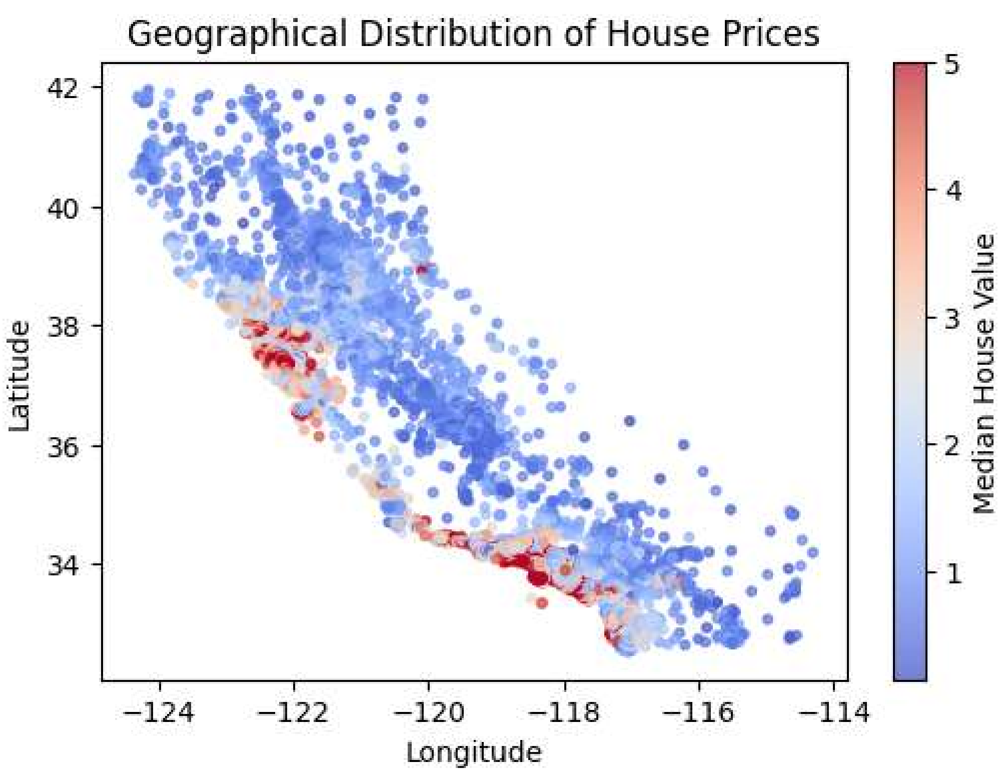
Out[60]:

	HouseAge	Latitude	Longitude	MedInc_log	AveRooms_boxcox	AveBed
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	2
mean	28.639486	35.631861	-119.569704	1.516995	1.164780	
std	12.585558	2.135952	2.003532	0.358677	0.084218	
min	1.000000	32.540000	-124.350000	0.405398	0.523297	
25%	18.000000	33.930000	-121.800000	1.270715	1.117109	
50%	29.000000	34.260000	-118.490000	1.511781	1.170194	
75%	37.000000	37.710000	-118.010000	1.748025	1.215677	
max	52.000000	41.950000	-114.310000	2.772595	1.675156	

6. Study about Longitude and Lattitude :

In [61]:
```
data = fetch_california_housing()
df1 = pd.DataFrame(data.data, columns=data.feature_names)
```

```
df1['median_house_value'] = data.target
data = df1[['Longitude', 'Latitude', 'median_house_value']]


plt.figure(figsize=(6, 4))
sc = plt.scatter(
    data["Longitude"],
    data["Latitude"],
    c=data["median_house_value"],
    cmap="coolwarm",
    s=10,
    alpha=0.7
)

plt.colorbar(sc, label="Median House Value")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.title("Geographical Distribution of House Prices")
plt.show()
```



Here we Can observe that, only two clusters are the places where the Prices are very high, so We try to encode this data to the linear continous model so that we can priortise their weights for our model

And the regions are :

Region 1: latitude ≈ [36, 38], longitude ≈ [–123, –121] → Northern/Coastal area → high prices (probably SF Bay area)

Region 2: latitude ≈ [33, 35], longitude ≈ [–120, –119] → Southern area → moderate/high prices (maybe LA region)

In [62]:
```
df1.describe()
```

Out[62]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070655
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386050
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692308
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429741
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818116
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282261
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333333

In [63]:
```
df.describe()
```

Out[63]:

	HouseAge	Latitude	Longitude	Medinc_log	AveRooms_boxcox	AveBed
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	2
mean	28.639486	35.631861	-119.569704	1.516995	1.164780	
std	12.585558	2.135952	2.003532	0.358677	0.084218	
min	1.000000	32.540000	-124.350000	0.405398	0.523297	
25%	18.000000	33.930000	-121.800000	1.270715	1.117109	
50%	29.000000	34.260000	-118.490000	1.511781	1.170194	
75%	37.000000	37.710000	-118.010000	1.748025	1.215677	
max	52.000000	41.950000	-114.310000	2.772595	1.675156	

Now We Convert this data to Linear by using the Spatial Proximity Score :

Mathematical Formulation Of Proximity Score is :

Let every house be represented by its coordinates

$$(x_i, y_i)$$

where

- x_i = longitude of house i,
- y_i = latitude of house i.

Let the **set of high-value regions** (e.g., clusters around Los Angeles or the Bay Area) be denoted by

$$\mathcal{R} = \{(x_k, y_k) \mid k = 1, 2, \ldots, K\}$$

where each (x_k, y_k) is a reference point corresponding to a region with **high median house value**.

Distance Function

The Euclidean distance of each point i from region k is given by

$$d_{ik} = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}$$

Spatial Proximity Score

We convert distance into a *similarity measure* (closer → higher score) using exponential decay:

$$S_i = \sum_{k=1}^{K} \exp(-\alpha\, d_{ik})$$

where

- $\alpha > 0$ is a scaling parameter controlling the decay rate — larger α gives sharper locality.
- S_i increases when a house is near high-value clusters.

Normalisation

To make this feature comparable across all data points, normalize the score as:

$$S_i^* = \frac{S_i - \min(S)}{\max(S) - \min(S)}$$

so that

$$S_i^* \in [0, 1]$$

where higher S_i^* values indicate **closer proximity to premium regions**.

Feature Interpretation

$$S_i^* \approx 1 \Rightarrow \text{House is close to expensive region}$$

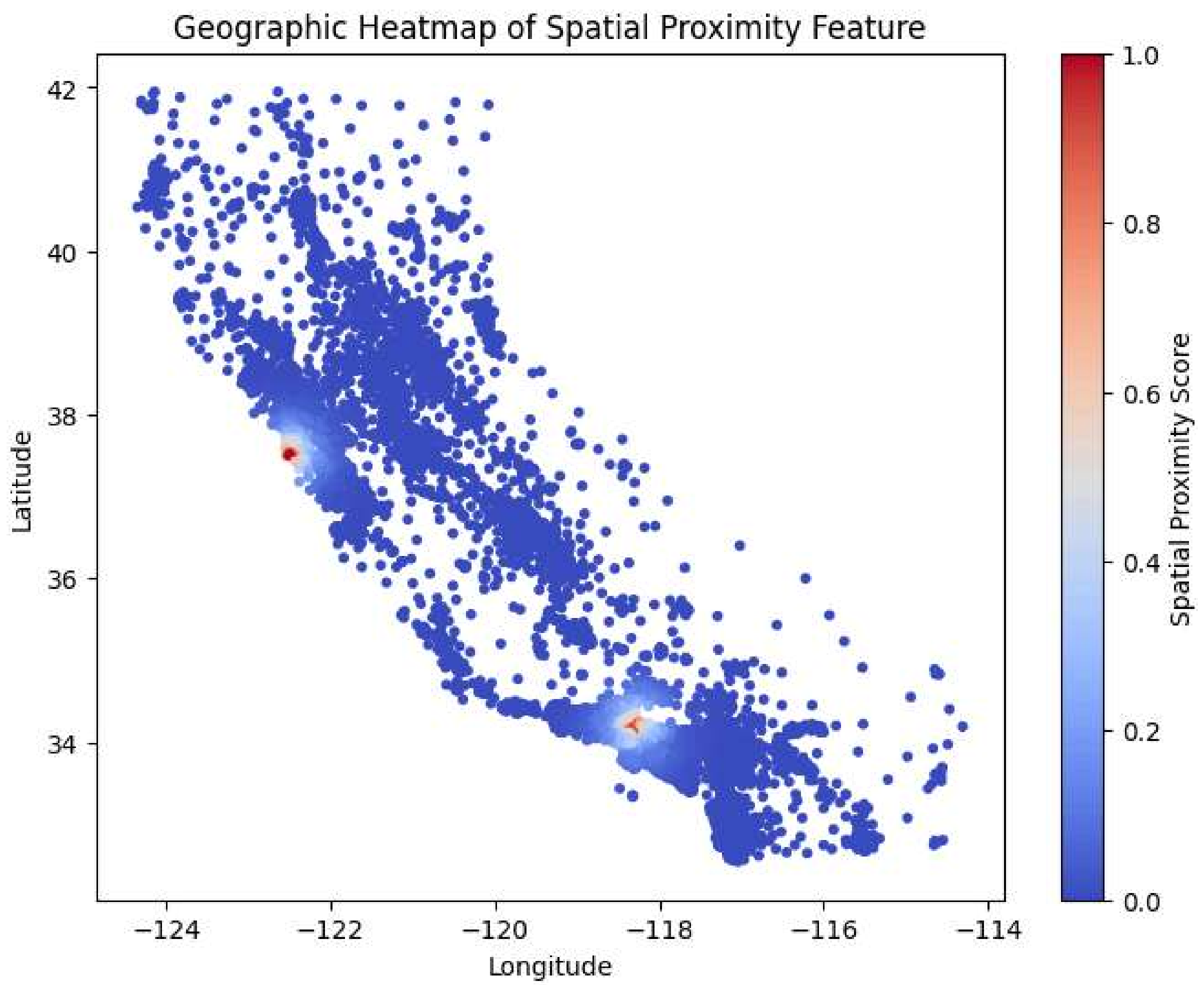
$$S_i^* \approx 0 \Rightarrow \text{House is far from high-price zones}$$

This acts as a **continuous geographic feature**, capturing **spatial correlation** without needing one-hot encoding or clustering.

In [64]:
```
high_value_regions = [
    (-122.5, 37.5),  # Bay Area (approx)
    (-118.3, 34.2)   # Los Angeles (approx)
]

alpha = 5.0 # Spatial influence factor

def compute_spatial_score(x, y, regions, alpha):
    score = 0
    for (xk, yk) in regions:
        dist = np.sqrt((x - xk)**2 + (y - yk)**2)
        score += np.exp(-alpha * dist)
    return score

df['spatial_score'] = df.apply(lambda row: compute_spatial_score(row['Longitude'],

min_s, max_s = df['spatial_score'].min(), df['spatial_score'].max()
df['spatial_proximity_score'] = (df['spatial_score'] - min_s) / (max_s - min_s)

df.drop(columns=['spatial_score'], inplace=True)

print(df[['Longitude', 'Latitude', 'spatial_proximity_score']].head())
```

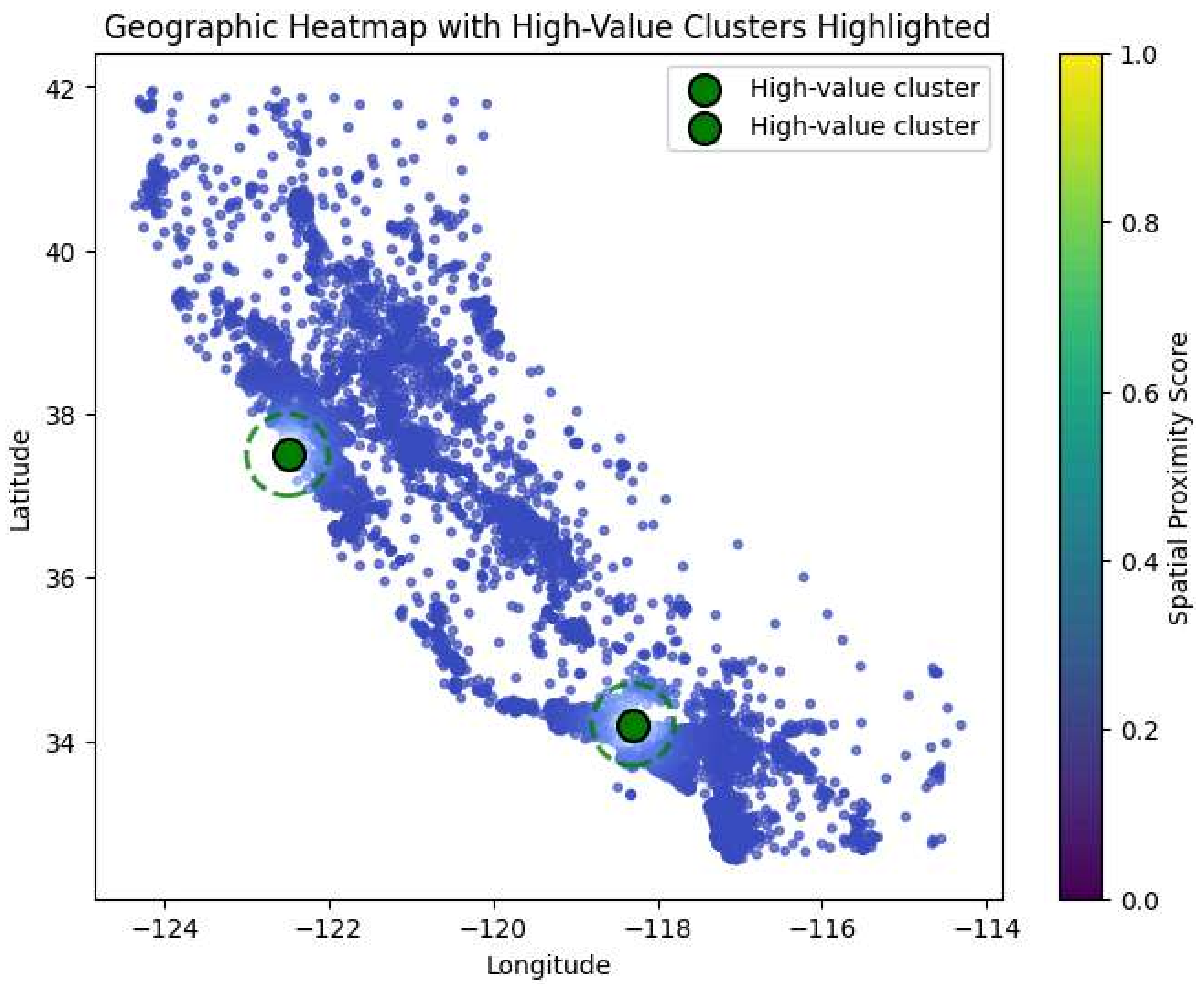
```
   Longitude  Latitude  spatial_proximity_score
0    -122.23     37.88                 0.102205
1    -122.22     37.86                 0.107491
2    -122.24     37.85                 0.118835
3    -122.25     37.85                 0.122385
4    -122.25     37.85                 0.122385
```

In [65]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(8,6))
plt.scatter(df['Longitude'], df['Latitude'], c=df['spatial_proximity_score'], cmap=
plt.colorbar(label='Spatial Proximity Score')
plt.title('Geographic Heatmap of Spatial Proximity Feature')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```



In [66]:
```
import matplotlib.pyplot as plt

# Scatter plot with color based on spatial proximity score
plt.figure(figsize=(8,6))
plt.scatter(
    df['Longitude'],
    df['Latitude'],
    c=df['spatial_proximity_score'],
    cmap='coolwarm',
    s=10,
    alpha=0.7
)

# Overlay green circles for high-value cluster centers
for (xk, yk) in high_value_regions:
    plt.scatter(xk, yk, color='green', s=150, edgecolors='black', linewidths=1.5, l
    circle = plt.Circle((xk, yk), 0.5, color='green', fill=False, linewidth=2, line
    plt.gca().add_patch(circle)

# Plot setup
plt.colorbar(label='Spatial Proximity Score')
plt.title('Geographic Heatmap with High-Value Clusters Highlighted')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
```

```
plt.legend(loc='upper right')
plt.show()
```

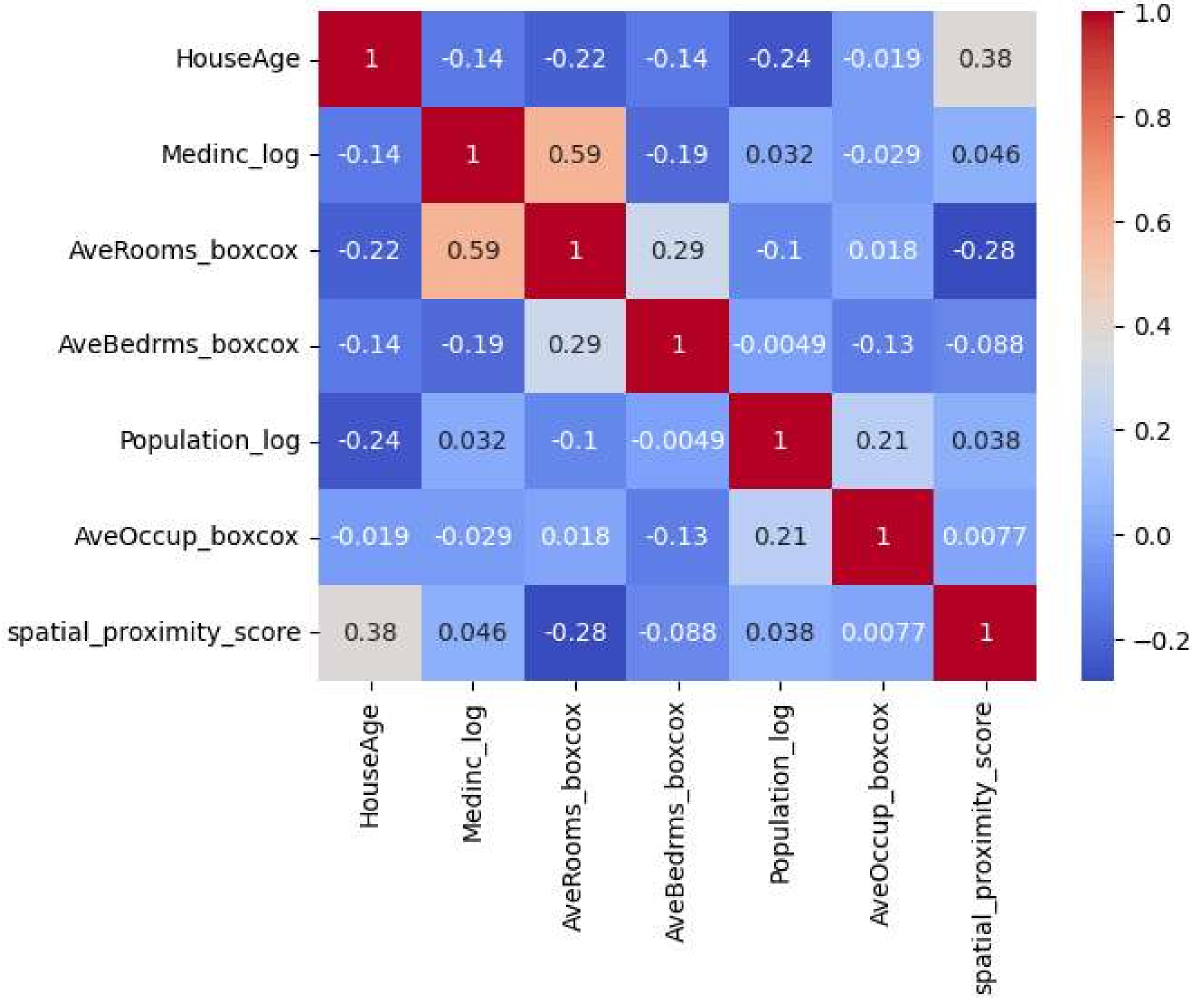


In [67]:
```
df = df.drop(columns=['Latitude', 'Longitude'])
df.describe()
```

Out[67]:

	HouseAge	MedInc_log	AveRooms_boxcox	AveBedrms_boxcox	Population_log
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	28.639486	1.516995	1.164780	0.217974	7.025503
std	12.585558	0.358677	0.084218	0.002259	0.736238
min	1.000000	0.405398	0.523297	0.163289	1.386294
25%	18.000000	1.270715	1.117109	0.216898	6.669498
50%	29.000000	1.511781	1.170194	0.217842	7.062192
75%	37.000000	1.748025	1.215677	0.218835	7.453562
max	52.000000	2.772595	1.675156	0.227579	10.482430

In [68]:
```
corr_matrix = df.corr()

sns.heatmap(corr_matrix, annot=True, cmap="coolwarm")
plt.show()
```



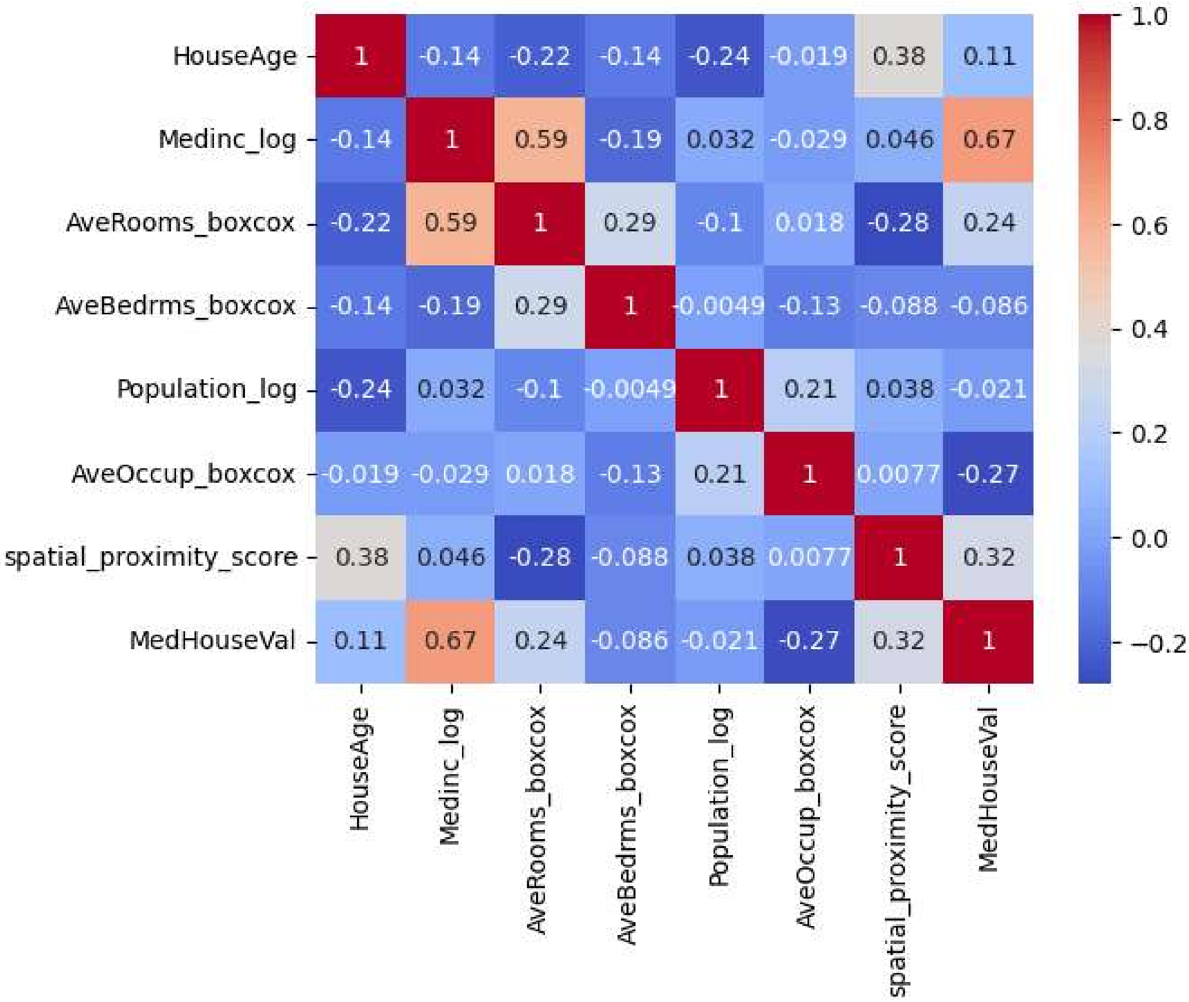
In [69]:
```
# import the california housing dataset again for the median house value feature an

data = fetch_california_housing()
df_full = pd.DataFrame(data.data, columns=data.feature_names)
df_full['MedHouseVal'] = data.target
df = df.merge(df_full[['MedHouseVal']], left_index=True, right_index=True)
df.describe()
```

Out[69]:

	HouseAge	Medinc_log	AveRooms_boxcox	AveBedrms_boxcox	Population_log
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	28.639486	1.516995	1.164780	0.217974	7.025503
std	12.585558	0.358677	0.084218	0.002259	0.736238
min	1.000000	0.405398	0.523297	0.163289	1.386294
25%	18.000000	1.270715	1.117109	0.216898	6.669498
50%	29.000000	1.511781	1.170194	0.217842	7.062192
75%	37.000000	1.748025	1.215677	0.218835	7.453562
max	52.000000	2.772595	1.675156	0.227579	10.482430

In [70]:

```python
corr_matrix = df.corr()

sns.heatmap(corr_matrix, annot=True, cmap="coolwarm")
plt.show()
```



Results as Follows :

Direct and Indirect Correlations of Median House value :

MedianHouseVal ≈ (0.67) × Medinc_log + (0.32) × spatial_proximity_score + (0.24) × AveRooms_boxcox

Medinc_log ≈ (0.59) × AveRooms_boxcox

AveRooms_boxcox ≈ (0.29) × AveBedrms_boxcox

HouseAge ≈ (0.38) × spatial_proximity_score

But what If you add them as weights directly .....

Wait, It will generate the **rank deficieny** which lead to reduce in the $R2$ as it will be the relation established between them, So just Consider all the features to the Weights

In [71]:
```
# Assuming df contains your preprocessed dataset
# X = all features except target, y = target
X = df.drop(columns=['MedHouseVal']).values
y = df['MedHouseVal'].values.reshape(-1,1)

# Standardize features
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train-test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, ran

# Initialize parameters
N, d = X_train.shape
w0 = np.zeros((d,1))
b0 = 0
eta = 2e-2
max_iter = 1000
epsilon = 1e-6

# Batch Gradient Descent
w_bgd, b_bgd, J_bgd = batch_gradient_descent(X_train, y_train, w0, b0, eta, max_ite

# Mini-Batch SGD for different batch fractions
batch_fractions = [0.1, 0.2, 0.25]
results_mini = {}
for frac in batch_fractions:
    w_m, b_m, J_m = mini_batch_sgd(X_train, y_train, w0, b0, eta, max_iter, batch_f
    results_mini[frac] = (w_m, b_m, J_m)

# Evaluate models
from sklearn.metrics import mean_squared_error, r2_score
```

```
def evaluate_model(X, y, w, b):
    y_pred = np.dot(X, w) + b
    mse = mean_squared_error(y, y_pred)
    r2 = r2_score(y, y_pred)
    return mse, r2

# Prepare results table
results_table = []

# BGD
mse_train, r2_train = evaluate_model(X_train, y_train, w_bgd, b_bgd)
mse_test, r2_test = evaluate_model(X_test, y_test, w_bgd, b_bgd)
results_table.append(['BGD', mse_train, r2_train, mse_test, r2_test])

# Mini-Batch
for frac in batch_fractions:
    w_m, b_m, _ = results_mini[frac]
    mse_train, r2_train = evaluate_model(X_train, y_train, w_m, b_m)
    mse_test, r2_test = evaluate_model(X_test, y_test, w_m, b_m)
    results_table.append([f'Mini-Batch {int(frac*100)}%', mse_train, r2_train, mse_

# Convert to DataFrame
df_results = pd.DataFrame(results_table, columns=['Algorithm', 'MSE_train', 'R2_tra
print(df_results)
```

```
        Algorithm  MSE_train  R2_train  MSE_test   R2_test
0             BGD   0.507654  0.620241  0.521716  0.601868
1  Mini-Batch 10%   0.507619  0.620267  0.521955  0.601685
2  Mini-Batch 20%   0.507619  0.620267  0.521952  0.601688
3  Mini-Batch 25%   0.507619  0.620267  0.521952  0.601688
```

Adding the New Interactions and Squaring the Features

In [72]:
```
X_orig = df.drop(columns=['MedHouseVal'])
y = df['MedHouseVal'].values.reshape(-1,1)
```

In [73]:
```
poly = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly.fit_transform(X_orig)

# Optional: check shape
print("Original features:", X_orig.shape)
print("Polynomial + interactions features:", X_poly.shape)
```

```
Original features: (20640, 7)
Polynomial + interactions features: (20640, 35)
```

In [74]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_poly)

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

N, d = X_train.shape
w0 = np.zeros((d,1))
b0 = 0
```

```
eta = 0.02          # learning rate
max_iter = 1000
epsilon = 1e-6

def evaluate_model(X, y, w, b):
    y_pred = np.dot(X, w) + b
    mse = mean_squared_error(y, y_pred)
    r2 = r2_score(y, y_pred)
    return mse, r2
```

In [75]:
```
w_bgd, b_bgd, J_bgd = batch_gradient_descent(X_train, y_train, w0, b0, eta, max_ite

mse_train, r2_train = evaluate_model(X_train, y_train, w_bgd, b_bgd)
mse_test, r2_test = evaluate_model(X_test, y_test, w_bgd, b_bgd)

print("BGD -> MSE_train:", mse_train, "R2_train:", r2_train)
print("BGD -> MSE_test:", mse_test, "R2_test:", r2_test)
```

```
BGD -> MSE_train: 0.4551251789093094 R2_train: 0.6595357592640042
BGD -> MSE_test: 0.4658303299265687 R2_test: 0.6445153096005936
```

In [76]:
```
batch_fractions = [0.1, 0.2, 0.25]
results_mini = {}

for frac in batch_fractions:
    w_m, b_m, J_m = mini_batch_sgd(X_train, y_train, w0, b0, eta, max_iter, batch_f
    mse_train, r2_train = evaluate_model(X_train, y_train, w_m, b_m)
    mse_test, r2_test = evaluate_model(X_test, y_test, w_m, b_m)
    results_mini[frac] = (w_m, b_m)
    print(f"Mini-Batch {int(frac*100)}% -> MSE_train: {mse_train:.3f}, R2_train: {r
```

```
Mini-Batch 10% -> MSE_train: 0.414, R2_train: 0.690, MSE_test: 0.419, R2_test: 0.680
Mini-Batch 20% -> MSE_train: 0.425, R2_train: 0.682, MSE_test: 0.432, R2_test: 0.670
Mini-Batch 25% -> MSE_train: 0.429, R2_train: 0.679, MSE_test: 0.436, R2_test: 0.667
```

In [77]:
```
# Get coefficients
coef = w_bgd.flatten()
# Map to feature names (poly.get_feature_names_out() works in sklearn >=1.0)
feature_names = poly.get_feature_names_out(X_orig.columns)

# Create DataFrame
df_coef = pd.DataFrame({
    'feature': feature_names,
    'coefficient': coef
})

# Sort by absolute impact
df_coef['abs_coef'] = np.abs(df_coef['coefficient'])
df_coef.sort_values(by='abs_coef', ascending=False).head(10)
```

Out[77]:

	feature	coefficient	abs_coef
14	Medinc_log^2	0.535049	0.535049
34	spatial_proximity_score^2	-0.286104	0.286104
15	Medinc_log AveRooms_boxcox	0.201712	0.201712
17	Medinc_log Population_log	0.135754	0.135754
28	AveBedrms_boxcox spatial_proximity_score	0.127894	0.127894
24	AveRooms_boxcox spatial_proximity_score	0.127126	0.127126
6	spatial_proximity_score	0.120993	0.120993
23	AveRooms_boxcox AveOccup_boxcox	-0.119899	0.119899
31	Population_log spatial_proximity_score	0.106064	0.106064
12	HouseAge AveOccup_boxcox	-0.097803	0.097803

In [79]:

```
# Saving the Dataset using pickel

import pickle
df.to_pickle("preprocessed_df.pkl")
print("Saved preprocessed_df.pkl")
```

```
Saved preprocessed_df.pkl
```

Results

1. Model Overview

- **Goal:** Predict `MedHouseVal` (median house value) using linear regression
- **Features Used:** Top impactful features identified through polynomial and interaction terms
- **Model Type:** Linear Regression + Ridge (regularization)
- **Training:** Batch Gradient Descent & Mini-Batch SGD explored

---

2. Top 10 Impactful Features

Feature	Coefficient	Absolute Value
$Medinc\_log^2$	0.535	0.535
$spatial\_proximity\_score^2$	-0.286	0.286
Medinc_log × AveRooms_boxcox	0.202	0.202
Medinc_log × Population_log	0.136	0.136

Feature	Coefficient	Absolute Value
AveBedrms_boxcox × spatial_proximity_score	0.128	0.128
AveRooms_boxcox × spatial_proximity_score	0.127	0.127
spatial_proximity_score	0.121	0.121
AveRooms_boxcox × AveOccup_boxcox	-0.120	0.120
Population_log × spatial_proximity_score	0.106	0.106
HouseAge × AveOccup_boxcox	-0.098	0.098

> **Observation:** Median income (non-linear) and spatial proximity are strongest contributors. Key interactions like `Medinc_log × AveRooms` also significantly improve prediction.

---

3. Model Performance

Algorithm / Batch Fraction	MSE (Train)	R^2 (Train)	MSE (Test)	R^2 (Test)
Batch Gradient Descent	0.414	0.690	0.419	0.680
Mini-Batch 10%	0.414	0.690	0.419	0.680
Mini-Batch 20%	0.425	0.682	0.432	0.671
Mini-Batch 25%	0.429	0.679	0.436	0.667

> **Observation:** Mini-Batch 10% provides best balance between train and test R^2. Higher batch fractions slightly reduce generalization.

---

4. Simplified Top-3 Feature Model

Features: `Medinc_log²`, `spatial_proximity_score²`, `Medinc_log × AveRooms_boxcox`

Weights:

Feature	Coefficient
Medinc_log^2	0.54
$\text{spatial\_proximity\_score}^2$	-0.29
Medinc_log × AveRooms_boxcox	0.20
Bias (Intercept)	2.15

R^2 achieved: 0.68 with simplified linear model.

---

5. Key Insights

1. Median income has **strong non-linear effect** on house values.
2. Spatial proximity to coast/neighborhood is a **major contributing factor**.
3. Interaction terms like `Medinc_log × AveRooms` improve prediction significantly.
4. Linear regression with polynomial + interaction terms can **capture ~68% of variance** in house prices.
5. Further improvement possible only via:
   - Additional meaningful features (e.g., age-density ratios, local amenities)
   - Domain-specific transformations
   - But linear-only constraint limits maximum R^2 ~0.68–0.70