linear_regression

August 5, 2024

0.0.1 ML-A1 Implementation of Linear regression

- Instructions
  - Prepare a report to present your findings
  - Write a python code to implement stochastic gradient descent from scratch for the given house price prediction dataset.
  - Write a python code to implement stochastic gradient descent using scikit-learn for the given data and compare the output.
  - Write a python code to implement batch gradient descent from scratch and also using scikit-lean for the given house price prediction.
  - Compare the output of all the implementations and write conclusion.

  Dataset: House Price Prediction Challenge (kaggle.com)
- Submission Intruction:
  - Submission should include python notebook file for all the implementations.
  - There must be a report pdf file to illustrate your data science lifecycle implementation and present your finds. Report must not exceed 10 page or 1500 words.

Table of Content

Data Ingestion/Loading

- Load the necessary modules
- Load the data
- process the data

0.1 Stocastic Gradient Descent Implmentation

[ ]:
```python
# loading the library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split

plt.rcParams['figure.figsize'] = (18,6)


np.random.seed(32)
# data path
train_data  = "/home/suman/Applied-Machine-Learning/Linear Regression/train.csv"
test_data = "/home/suman/Applied-Machine-Learning/Linear Regression/test.csv"

# load the train and test data
df_train  = pd.read_csv(train_data)
df_test = pd.read_csv(test_data)

df_train.head()
```

[ ]:
```
  POSTED_BY  UNDER_CONSTRUCTION  RERA  BHK_NO. BHK_OR_RK    SQUARE_FT  \
0     Owner                   0     0        2       BHK  1300.236407
1    Dealer                   0     0        2       BHK  1275.000000
2     Owner                   0     0        2       BHK   933.159722
3     Owner                   0     1        2       BHK   929.921143
4    Dealer                   1     0        2       BHK   999.009247

   READY_TO_MOVE  RESALE                      ADDRESS  LONGITUDE   LATITUDE  \
0              1       1        Ksfc Layout,Bangalore  12.969910  77.597960
1              1       1    Vishweshwara Nagar,Mysore  12.274538  76.644605
2              1       1             Jigani,Bangalore  12.778033  77.632191
3              1       1  Sector-1 Vaishali,Ghaziabad  28.642300  77.344500
4              0       1             New Town,Kolkata  22.592200  88.484911

   TARGET(PRICE_IN_LACS)
0                   55.0
1                   51.0
2                   43.0
3                   62.5
4                   60.5
```

Data Understanding and Exploration The dataset used for this assignmetn is from Kaggle Dataset: House Price Prediction Challenge (kaggle.com)

- **Training Splits:** 29451 rows x 12 columns
- **Testing Splits:** 68720 x 11 columns
  - since we are using competition data testing data do not contain the labels, they are evaluated based on this splits.
- **Attributes of the Dataset**

Column	Description
POSTED_BY	Category marking who has listed the property
UNDER_CONSTRUCTION	Under Construction or Not
RERA	Rera approved or Not
BHK_NO	Number of Rooms
BHK_OR_RK	Type of property
SQUARE_FT	Total area of the house in square feet
READY_TO_MOVE	Category marking Ready to move or Not
RESALE	Category marking Resale or not
ADDRESS	Address of the property
LONGITUDE	Longitude of the property
LATITUDE	Latitude of the property

RERA stands for Real Estate (Regulation and Development) Act, which was enacted by the Indian government in 2016. It aims to protect home buyers and ensure transparency in the real estate sector. RERA establishes regulatory authorities at the state level to oversee real estate transactions and address grievances.

[ ]:
```
print(f'The train dataset contains {df_train.shape[0]} rows and {df_train.
↪shape[1]} columns.')
print(f'The test dataset contains {df_test.shape[0]} rows and {df_test.
↪shape[1]} columns.')
```

```
The train dataset contains 29451 rows and 12 columns.
The test dataset contains 68720 rows and 11 columns.
```

[ ]:
```
# info of the dateset
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29451 entries, 0 to 29450
Data columns (total 12 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   POSTED_BY              29451 non-null  object
 1   UNDER_CONSTRUCTION     29451 non-null  int64
 2   RERA                   29451 non-null  int64
```

```
 3   BHK_NO.                29451 non-null  int64
 4   BHK_OR_RK              29451 non-null  object
 5   SQUARE_FT              29451 non-null  float64
 6   READY_TO_MOVE          29451 non-null  int64
 7   RESALE                 29451 non-null  int64
 8   ADDRESS                29451 non-null  object
 9   LONGITUDE              29451 non-null  float64
 10  LATITUDE               29451 non-null  float64
 11  TARGET(PRICE_IN_LACS)  29451 non-null  float64
dtypes: float64(4), int64(5), object(3)
memory usage: 2.7+ MB
```

- since we are solving linear regression problem, the target or dependent variable must be continous and here we can see that it is continous
- rest we can see that there are total of three dtypes
- there are two categorical variable which are useful: `BHK_OR_RK` and `POSTED_BY`

Exploration and Descriptive Statistics

[ ]:
```
df_train.describe()
```

[ ]:
```
       UNDER_CONSTRUCTION          RERA       BHK_NO.     SQUARE_FT  \
count        29451.000000  29451.000000  29451.000000  2.945100e+04
mean             0.179756      0.317918      2.392279  1.980217e+04
std              0.383991      0.465675      0.879091  1.901335e+06
min              0.000000      0.000000      1.000000  3.000000e+00
25%              0.000000      0.000000      2.000000  9.000211e+02
50%              0.000000      0.000000      2.000000  1.175057e+03
75%              0.000000      1.000000      3.000000  1.550688e+03
max              1.000000      1.000000     20.000000  2.545455e+08

       READY_TO_MOVE       RESALE     LONGITUDE      LATITUDE  \
count   29451.000000  29451.000000  29451.000000  29451.000000
mean        0.820244      0.929578     21.300255     76.837695
std         0.383991      0.255861      6.205306     10.557747
min         0.000000      0.000000    -37.713008   -121.761248
25%         1.000000      1.000000     18.452663     73.798100
50%         1.000000      1.000000     20.750000     77.324137
75%         1.000000      1.000000     26.900926     77.828740
max         1.000000      1.000000     59.912884    152.962676

       TARGET(PRICE_IN_LACS)
count           29451.000000
mean              142.898746
std               656.880713
min                 0.250000
25%                38.000000
50%                62.000000
```

```
75%                  100.000000
max                30000.000000
```

[ ]:
```python
# categorical data

df_train.describe(exclude=["float", "int"])
```

[ ]:
```
       POSTED_BY BHK_OR_RK              ADDRESS
count      29451     29451                29451
unique         3         2                 6899
top       Dealer       BHK  Zirakpur,Chandigarh
freq       18291     29427                  509
```

[ ]:
```python
# check for null values
df_train.isnull().sum()
```

[ ]:
```
POSTED_BY                0
UNDER_CONSTRUCTION       0
RERA                     0
BHK_NO.                  0
BHK_OR_RK                0
SQUARE_FT                0
READY_TO_MOVE            0
RESALE                   0
ADDRESS                  0
LONGITUDE                0
LATITUDE                 0
TARGET(PRICE_IN_LACS)    0
dtype: int64
```

Interpretations:

- there are numerical and categorical variables
- the dataset have no missing records (since this is competition data it is already been curated)
- target/depedent variable is continous (as float dtype)

Basic EDA

[ ]:
```python
df_train['POSTED_BY'].value_counts()
```

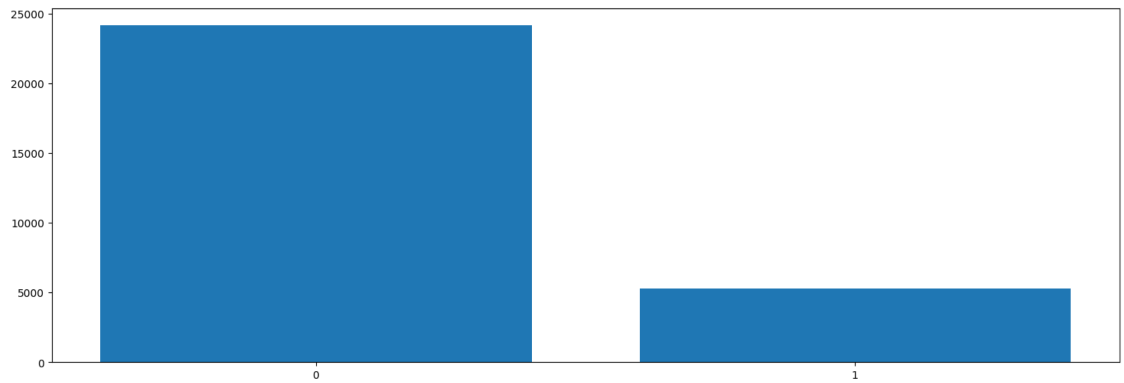
[ ]:
```
POSTED_BY
Dealer     18291
Owner      10538
Builder      622
Name: count, dtype: int64
```

[ ]:
```python
df_train['UNDER_CONSTRUCTION'].value_counts()
```

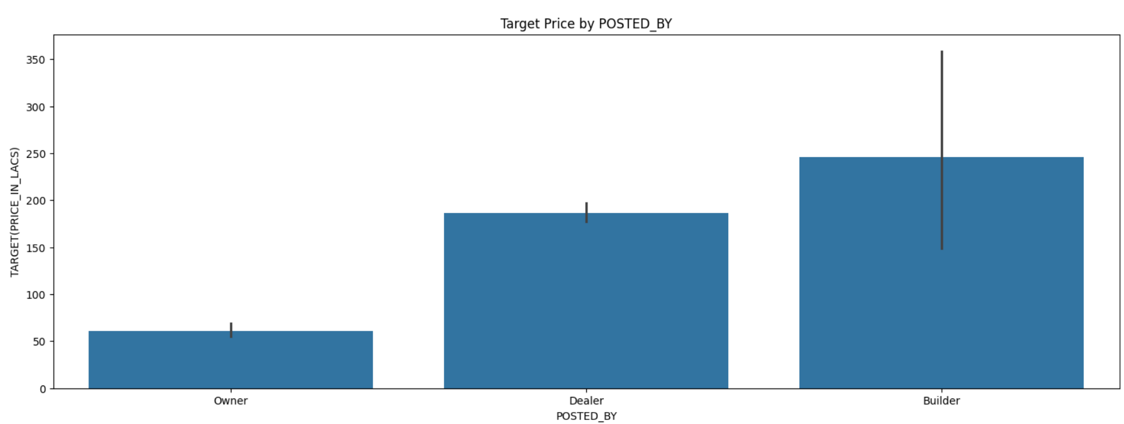
[ ]: UNDER_CONSTRUCTION
```
0    24157
1     5294
Name: count, dtype: int64
```

[ ]:
```python
plt.bar(["0","1"],df_train["UNDER_CONSTRUCTION"].value_counts())
```

[ ]: <BarContainer object of 2 artists>

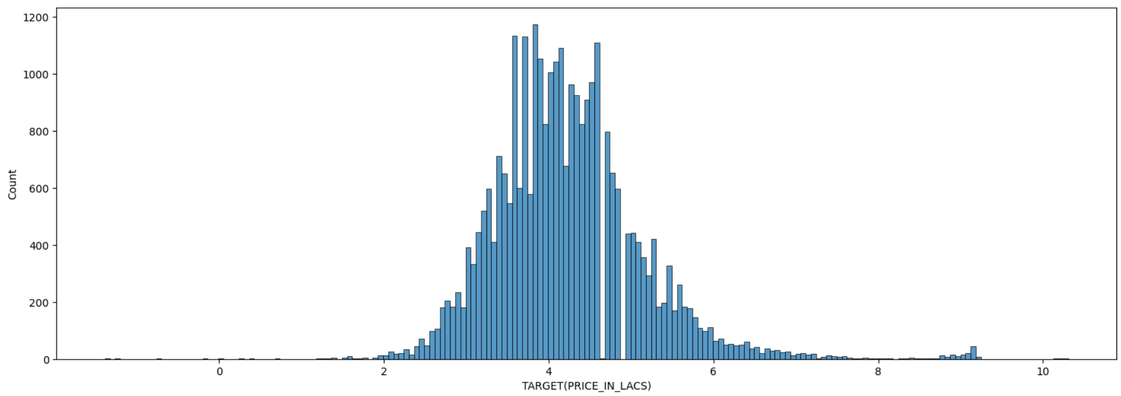


[ ]:
```python
sns.barplot(x='POSTED_BY', y='TARGET(PRICE_IN_LACS)', data=df_train)
plt.title('Target Price by POSTED_BY')
plt.show()

# looks like majority of the property listinga re made dealers
```



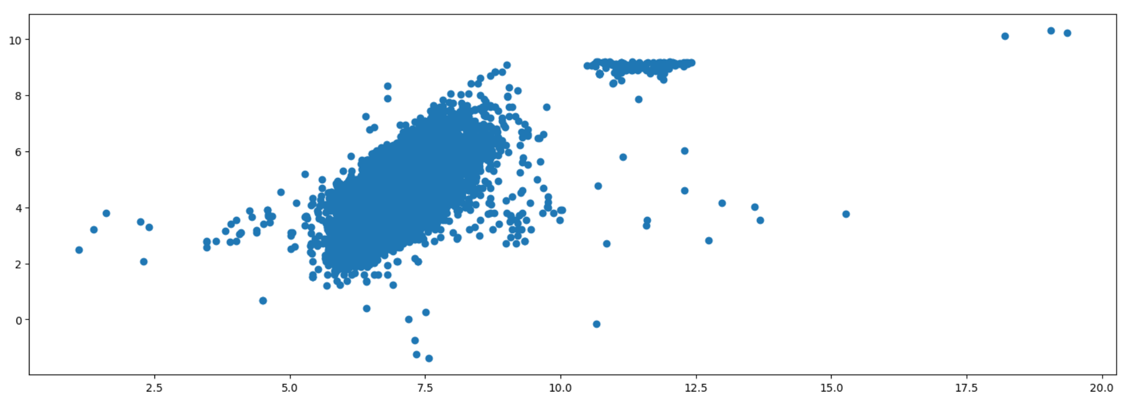
[ ]:
```python
sns.histplot(np.log(df_train["TARGET(PRICE_IN_LACS)"]))
```

[ ]: <Axes: xlabel='TARGET(PRICE_IN_LACS)', ylabel='Count'>



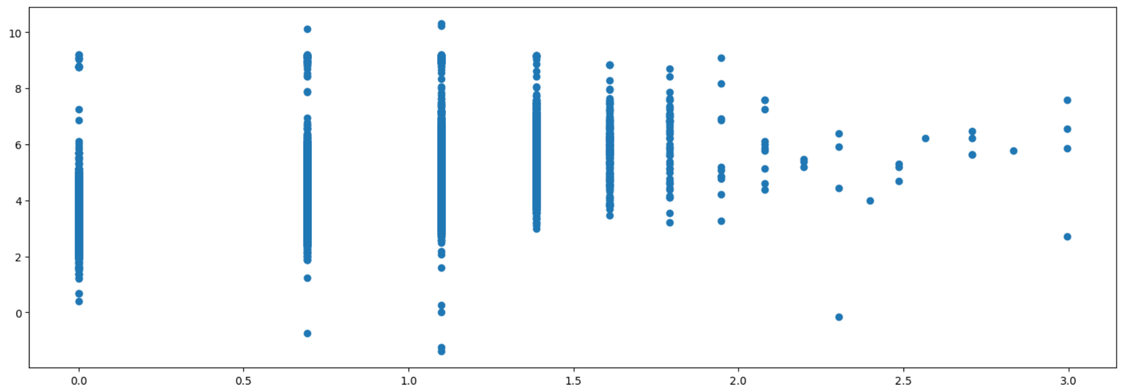

```
[ ]: # check the relationship between square ft and the price
     # does sqaure ft influences price?
     plt.scatter(x=np.log(df_train["SQUARE_FT"]), y=np.
      ↪log(df_train["TARGET(PRICE_IN_LACS)"]))

     # looks like it does
```

```
[ ]: <matplotlib.collections.PathCollection at 0x7f26d8896c90>
```



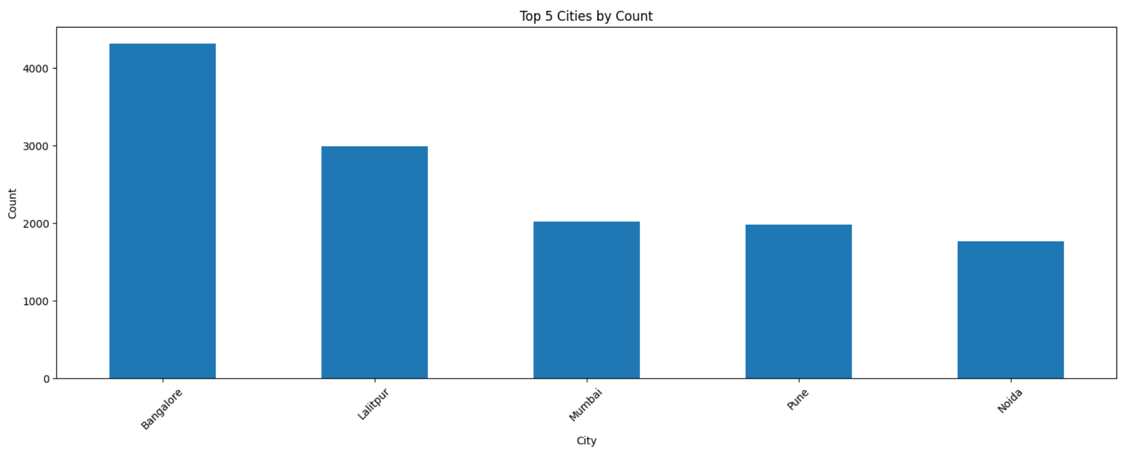

```
[ ]: plt.scatter(x=np.log(df_train["BHK_NO."]), y=np.
      ↪log(df_train["TARGET(PRICE_IN_LACS)"]))
```

```
[ ]: <matplotlib.collections.PathCollection at 0x7f26d873e9f0>
```



[ ]:
```
# which city is most popular?
new_df = df_train['ADDRESS'].str.split(',').str.get(1)
city_counts = new_df.value_counts().head(5)
```

[ ]:
```
city_counts.plot(kind='bar')
plt.title('Top 5 Cities by Count')
plt.xlabel('City')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



[ ]:
```
# make a copy so that we need not have to restart the notebook should we mess␣
↪up the data.
df_train_copy = df_train.copy()
```

Data Preprocessing

- Check Missing Data

    – since there is no missing data, we skip this part.
- Check any redundant data, if present drop them
- Standardization/Normalization
- Encoding the Categorical Variables

```
[ ]: df_train.duplicated().sum()
     print(f"There are {df_train[df_train.duplicated()].shape[0]} duplicates in␣
      ↪training dataset.")
```

```
There are 401 duplicates in training dataset.
```

```
[ ]: # let's drop the duplicates
     df_train.drop_duplicates(inplace=True)
```

```
[ ]: df_train.duplicated().sum()
```

```
[ ]: 0
```

```
[ ]: # now let's remove the uwanted columns, as they do
     df_train = df_train.drop(['ADDRESS'], axis=1)
```

Encoding Categorical Variable

```
[ ]: from sklearn.preprocessing import LabelEncoder
     from sklearn.pipeline import Pipeline
     from sklearn.compose import ColumnTransformer
     from sklearn.preprocessing import FunctionTransformer

     # Label encoding function
     def label_encoder(X):
         X_transformed = X.copy()
         for column in X.columns:
             le = LabelEncoder()
             X_transformed[column] = le.fit_transform(X[column])
         return X_transformed
```

```
[ ]: # Define the preprocessing steps for categorical features
     categorical_features = ['POSTED_BY', 'BHK_OR_RK']
     categorical_transformer = Pipeline(steps=[
         ('label_encoder', FunctionTransformer(label_encoder, validate=False))
     ])
```

Standardizing

```
[ ]: from sklearn.preprocessing import StandardScaler
```

```
[ ]: # Define the preprocessing steps for numerical features
     numerical_features_standard = ['BHK_NO.', 'SQUARE_FT', 'LONGITUDE', 'LATITUDE']
```

```
numerical_transformer_standard = Pipeline(steps=[
    ('standard_scaler', StandardScaler())
])
```

[ ]:
```
# Combine preprocessing steps
preprocessor = ColumnTransformer(
    transformers=[
        ('categorical', categorical_transformer, categorical_features),
        ('numerical', numerical_transformer_standard,␣
 ↪numerical_features_standard)
    ],
    remainder='passthrough'
)
```

Pipelining

[ ]:
```
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.model_selection import train_test_split
```

[ ]:
```
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', SGDRegressor(max_iter=1, tol=None, warm_start=True))
])
```

[ ]:
```
LABELS = 'TARGET(PRICE_IN_LACS)'
train_features = [col for col in df_train.columns if col not in [LABELS]]
train_data = df_train[train_features]
train_labels = df_train[LABELS]
```

Splitting the dataset

[ ]:
```
train_data, valid_data, train_labels, valid_labels =␣
 ↪train_test_split(train_data, train_labels, random_state=42, test_size = 0.2)

print(f"The shape of training dataset is: {train_data.shape}")
print(train_data.shape)


print(f"The shape of training dataset is: {train_data.shape}")
print(valid_data.shape)
```

```
The shape of training dataset is: (23240, 10)
(23240, 10)
The shape of training dataset is: (23240, 10)
(5810, 10)
```

```
[ ]: test_features = [col for col in df_test.columns if col not in [LABELS]]
     test_data = df_test[test_features]
```

Finding the best hyperparameters

```
[ ]: # initial search
     param_grid = {
         'regressor__loss': ['squared_error'],
         'regressor__penalty': ['l2', 'l1'],
         'regressor__alpha': [0.0001, 0.001, 0.01],
         'regressor__l1_ratio': [0.0, 0.1, 0.5],
         'regressor__eta0': [0.001, 0.01, 0.1],
     }
```

```
[ ]: from sklearn.model_selection import GridSearchCV
```

```
[ ]: grid_search = GridSearchCV(pipeline, param_grid, cv=5,
                                scoring='neg_mean_squared_error', n_jobs=-1)

     grid_search.fit(train_data, train_labels)
```

```
/home/suman/.conda/envs/documentai/lib/python3.12/site-
packages/sklearn/compose/_column_transformer.py:1623: FutureWarning:
The format of the columns of the 'remainder' transformer in
ColumnTransformer.transformers_ will change in version 1.7 to match the format
of the other transformers.
At the moment the remainder columns are stored as indices (of type int). With
the same ColumnTransformer configuration, in the future they will be stored as
column names (of type str).
To use the new behavior now and suppress this warning, use
ColumnTransformer(force_int_remainder_cols=False).

  warnings.warn(
```

```
[ ]: GridSearchCV(cv=5,
                  estimator=Pipeline(steps=[('preprocessor',
     ColumnTransformer(remainder='passthrough',
     transformers=[('categorical',
     Pipeline(steps=[('label_encoder',
               FunctionTransformer(func=<function label_encoder at
     0x7f26d8931800>))]),
     ['POSTED_BY',
     'BHK_OR_RK']),
     ('numerical',
     Pipeline(steps=[('standard_scaler',
               StandardScaler())]),
     ['BHK_NO.',
```

```
'SQUARE_FT',
'LONGITUDE',
'LATITUDE'])])),
                                        ('regressor',
                                         SGDRegressor(max_iter=1, tol=None,
                                                      warm_start=True))]),
             n_jobs=-1,
             param_grid={'regressor__alpha': [0.0001, 0.001, 0.01],
                         'regressor__eta0': [0.001, 0.01, 0.1],
                         'regressor__l1_ratio': [0.0, 0.1, 0.5],
                         'regressor__loss': ['squared_error'],
                         'regressor__penalty': ['l2', 'l1']},
             scoring='neg_mean_squared_error')
```

[ ]:
```
best_parameters = grid_search.best_params_
best_model = grid_search.best_estimator_

print(f'The best model is : {best_model} with parameters {best_parameters}')
```

```
The best model is : Pipeline(steps=[('preprocessor',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('categorical',
Pipeline(steps=[('label_encoder',
FunctionTransformer(func=<function label_encoder at 0x7f26d8931800>))]),
                                                  ['POSTED_BY', 'BHK_OR_RK']),
                                                 ('numerical',
Pipeline(steps=[('standard_scaler',
StandardScaler())]),
                                                  ['BHK_NO.', 'SQUARE_FT',
                                                   'LONGITUDE',
                                                   'LATITUDE'])])),
                ('regressor',
                 SGDRegressor(alpha=0.01, eta0=0.001, l1_ratio=0.1, max_iter=1,
                              tol=None, warm_start=True))]) with parameters
{'regressor__alpha': 0.01, 'regressor__eta0': 0.001, 'regressor__l1_ratio': 0.1,
'regressor__loss': 'squared_error', 'regressor__penalty': 'l2'}
```

[ ]:
```
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', SGDRegressor(alpha= 0.0001, eta0= 0.001, l1_ratio = 0.0,
                               loss= 'squared_error', penalty= 'l1',
                               tol= 0.01, max_iter=2000, warm_start=True))
])
```

Fit the model with best parameters and estimate

[ ]:
```
pipeline.fit(train_data, train_labels)
```

```
/home/suman/.conda/envs/documentai/lib/python3.12/site-
packages/sklearn/compose/_column_transformer.py:1623: FutureWarning:
The format of the columns of the 'remainder' transformer in
ColumnTransformer.transformers_ will change in version 1.7 to match the format
of the other transformers.
At the moment the remainder columns are stored as indices (of type int). With
the same ColumnTransformer configuration, in the future they will be stored as
column names (of type str).
To use the new behavior now and suppress this warning, use
ColumnTransformer(force_int_remainder_cols=False).

  warnings.warn(
```

[ ]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('categorical',
Pipeline(steps=[('label_encoder',
FunctionTransformer(func=<function label_encoder at 0x7f26d8931800>))]),
                                                  ['POSTED_BY', 'BHK_OR_RK']),
                                                 ('numerical',
Pipeline(steps=[('standard_scaler',
StandardScaler())]),
                                                  ['BHK_NO.', 'SQUARE_FT',
                                                   'LONGITUDE',
                                                   'LATITUDE'])])),
                ('regressor',
                 SGDRegressor(eta0=0.001, l1_ratio=0.0, max_iter=2000,
                              penalty='l1', tol=0.01, warm_start=True))])
```

[ ]:
```
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', SGDRegressor(alpha= 0.0001, eta0= 0.001, l1_ratio = 0.0,
                               loss= 'squared_error', penalty= 'l1',
                               tol= 0.01, max_iter=2000, warm_start=True))
])

pipeline.fit(train_data, train_labels)
```

```
/home/suman/.conda/envs/documentai/lib/python3.12/site-
packages/sklearn/compose/_column_transformer.py:1623: FutureWarning:
The format of the columns of the 'remainder' transformer in
ColumnTransformer.transformers_ will change in version 1.7 to match the format
of the other transformers.
At the moment the remainder columns are stored as indices (of type int). With
the same ColumnTransformer configuration, in the future they will be stored as
column names (of type str).
To use the new behavior now and suppress this warning, use
ColumnTransformer(force_int_remainder_cols=False).
```

```
warnings.warn(
```

```
[ ]: Pipeline(steps=[('preprocessor',
                  ColumnTransformer(remainder='passthrough',
                                    transformers=[('categorical',
     Pipeline(steps=[('label_encoder',
     FunctionTransformer(func=<function label_encoder at 0x7f26d8931800>))]),
                                                   ['POSTED_BY', 'BHK_OR_RK']),
                                                  ('numerical',
     Pipeline(steps=[('standard_scaler',
     StandardScaler())]),
                                                   ['BHK_NO.', 'SQUARE_FT',
                                                    'LONGITUDE',
                                                    'LATITUDE'])])),
                 ('regressor',
                  SGDRegressor(eta0=0.001, l1_ratio=0.0, max_iter=2000,
                               penalty='l1', tol=0.01, warm_start=True))])
```

Evaluation of the model

```
[ ]: y_hat = pipeline.predict(valid_data)
     print(f'Mean Squared Error: {mean_squared_error(valid_labels, y_hat)}')
     mean_squared_error_sgd = mean_squared_error(valid_labels, y_hat)
```

```
Mean Squared Error: 378435.8539077567
```

```
[ ]: print(f'Mean Absolute Error: {mean_absolute_error(valid_labels, y_hat)}')
```

```
Mean Absolute Error: 135.96579072419206
```

```
[ ]: print(f'Root Mean Square Error: {np.sqrt(mean_squared_error(valid_labels,␣
      ↪y_hat))}')
     root_mean_absolute_error = np.sqrt(mean_squared_error(valid_labels, y_hat))
```

```
Root Mean Square Error: 615.1714020561723
```

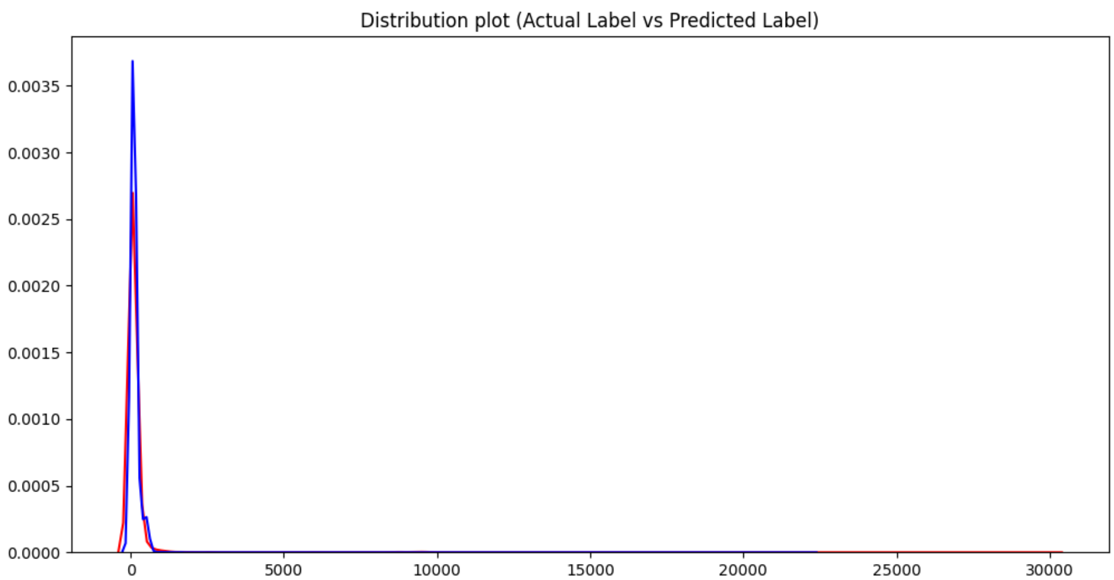
```
[ ]: print(f'R2 score is : {r2_score(valid_labels, y_hat)}')

     r2_sgd_linear = r2_score(valid_labels, y_hat)
```

```
R2 score is : 0.3088774233519437
```

```
[ ]: def show_distribution_plot(y_true, y_pred, xlabel="", ylabel=""):
       plt.figure(figsize=(12, 6))
       ax1 = sns.kdeplot(y_true, color='r', label='Actual value')
       sns.kdeplot(y_pred, color='b', label='Fitted value', ax=ax1)
```

```
    plt.title('Distribution plot (Actual Label vs Predicted Label)')
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)

    plt.show()
```

[ ]:
```
show_distribution_plot(valid_labels, y_hat)
```



Prediction

[ ]:
```
pred = pipeline.predict(test_data)
```

[ ]:
```
neg_index = np.where(pred < 0)
pred[neg_index] = np.abs(pred[neg_index])
```

[ ]:
```
pred
```

[ ]:
```
array([ 39.31517246, 478.74386283,  44.85543851, …, 394.81795119,
        84.4035233 , 170.04528112])
```

0.2 Stocastic Gradient Descent from Scratch

Algorithm Certainly! Here's the algorithm for Stochastic Gradient Descent (SGD):

1. **Initialize Parameters**:
   - Set initial values for parameters ( ).
   - Choose learning rate ( ) (step size).
2. **Repeat Until Convergence**:
   - Shuffle the dataset if necessary (optional for each epoch).

- For each data point ((x__i, y__i)) in the dataset:
    1. Compute the gradient of the loss function with respect parameters
    2. Update the parameters using the gradients
3. **Return**:
    - The optimized parameters

[ ]:
```
import numpy as np
from tqdm import  tqdm
from sklearn.utils import shuffle

class LinearRegression:
  def __init__(self,
               lr: float=0.001,
               epoch: int=10,
               clip_threshold: int=1):
    self.lr = lr
    self.epoch = epoch
    self.clip_threshold = clip_threshold

  def initialize_params(self, X):
    self.weights = np.random.randn(X.shape[1]) * (0.01)
    self.bias = 0

  def shuffle_data(self, X, y):
    X_shuffled, y_shuffled = shuffle(X, y, random_state=42)
    return X_shuffled, y_shuffled

  def compute_loss(self, X, Y=None):
    Y_hat = self.weights @ X.T + self.bias
    self.loss = (Y - Y_hat)**2 if Y else None
    return self.loss, Y_hat

  def get_error(self, Y, Y_hat):
    return (Y-Y_hat)

  def gradient_clipping(self, weights_grad, bias_grad):
    weights_grad = np.clip(weights_grad, -self.clip_threshold, self.
↪clip_threshold)
    bias_grad = np.clip(bias_grad, -self.clip_threshold, self.clip_threshold)

    return weights_grad, bias_grad

  def update_params(self, X, Y, Y_hat):
    error = self.get_error(Y, Y_hat)
    self.bias += (self.lr * error)
    self.weights += (self.lr * error * X)
```

```
  def print_training_stats(self, **kwargs):
    epoch = kwargs["epoch"]
    batch = kwargs["batch"]
    loss = kwargs["loss"]

    print(f"Epoch: {epoch}, Batch: {batch} Loss: {loss}")


  def fit(self, X, Y):
    self.initialize_params(X)
    for i in tqdm(range(self.epoch)):

      print(f"Epoch: {i + 1}")
      X, Y = self.shuffle_data(X, Y)
      total_loss = 0
      for j in range(X.shape[0]):
        loss, Y_hat = self.compute_loss(X[j], Y[j])
        self.update_params(X[j], Y[j], Y_hat)
        total_loss += loss
      print(f"loss: {total_loss/X.shape[0]}")

  def predict(self, X):
    _, Y_hat = self.compute_loss(X)
    return Y_hat
```

[ ]:
```
def preprocess_for_lrsgd_scratch(df_train):
    dummy = pd.get_dummies(df_train["BHK_OR_RK"], dtype="int")
    df_train = pd.concat([df_train, dummy], axis=1)
    df_train.drop(["BHK_OR_RK"], axis=1, inplace=True)
    feature_names_test = ["UNDER_CONSTRUCTION", "RERA", "BHK_NO.", "SQUARE_FT",␣
 ↪"READY_TO_MOVE", "RESALE", "BHK", "RK"]
    feature_names_train = feature_names_test + ["TARGET(PRICE_IN_LACS)"]

    df_train = df_train[feature_names_train]

    X = df_train.drop("TARGET(PRICE_IN_LACS)", axis=1).values
    y = df_train["TARGET(PRICE_IN_LACS)"].values

    X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

    return X_train, X_val, y_train, y_val
```

[ ]:
```
X_train, X_val, y_train, y_val = preprocess_for_lrsgd_scratch(df_train)
scaler = StandardScaler()
scaler = scaler.fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_val_scaled = scaler.transform(X_val)
```

[ ]:
```
lr_model = LinearRegression(lr=0.00001, epoch=100, clip_threshold=1)
lr_model.fit(X_train_scaled, y_train)
```

```
  2%|          | 2/100 [00:00<00:08, 11.18it/s]

Epoch: 1
loss: 398082.0059761518
Epoch: 2
loss: 366873.8741713837
Epoch: 3

  4%|          | 4/100 [00:00<00:08, 11.50it/s]

loss: 348147.48470447626
Epoch: 4
loss: 336518.01060937624
Epoch: 5
loss: 329532.09394238767
Epoch: 6

  8%|          | 8/100 [00:00<00:08, 11.47it/s]

loss: 325388.45313743973
Epoch: 7
loss: 322786.16056101146
Epoch: 8
loss: 321273.5136521538
Epoch: 9

 10%|          | 10/100 [00:00<00:07, 11.68it/s]

loss: 320282.3256626343
Epoch: 10
loss: 319677.7103163322
Epoch: 11
loss: 319322.94495276886
Epoch: 12

 14%|          | 14/100 [00:01<00:07, 11.41it/s]

loss: 319107.0522091822
Epoch: 13
loss: 318918.7682779178
Epoch: 14
loss: 318803.01698411186
Epoch: 15
```

```
 16%|          | 16/100 [00:01<00:07, 11.44it/s]

loss: 318787.15276643174
Epoch: 16
loss: 318713.4614113069
Epoch: 17
loss: 318736.9831966689
Epoch: 18

 20%|          | 20/100 [00:01<00:06, 11.48it/s]

loss: 318683.8894917791
Epoch: 19
loss: 318718.14276049635
Epoch: 20
loss: 318713.0717383057
Epoch: 21

 22%|          | 22/100 [00:01<00:06, 11.43it/s]

loss: 318704.7638582336
Epoch: 22
loss: 318661.17496370664
Epoch: 23
loss: 318705.73558510304
Epoch: 24

 24%|          | 24/100 [00:02<00:06, 11.34it/s]

loss: 318664.5439805045
Epoch: 25
loss: 318704.1270628956
Epoch: 26

 27%|          | 27/100 [00:02<00:09,  7.97it/s]

loss: 318701.9507716152
Epoch: 27
loss: 318704.0528098158
Epoch: 28

 29%|          | 29/100 [00:02<00:08,  8.30it/s]

loss: 318695.9677790185
Epoch: 29
loss: 318650.8675522994
Epoch: 30

 32%|          | 32/100 [00:03<00:07,  9.22it/s]

loss: 318661.2018293319
Epoch: 31
loss: 318702.35189181846
Epoch: 32
```

```
loss: 318663.50822404714
Epoch: 33

 34%|          | 34/100 [00:03<00:06,  9.79it/s]

loss: 318669.5845064966
Epoch: 34
loss: 318716.4469322137
Epoch: 35
loss: 318666.21664600825
Epoch: 36

 38%|          | 38/100 [00:03<00:05, 10.64it/s]

loss: 318660.4948813982
Epoch: 37
loss: 318679.0671913677
Epoch: 38
loss: 318678.82853843353
Epoch: 39

 40%|          | 40/100 [00:03<00:05, 10.80it/s]

loss: 318711.2205568495
Epoch: 40
loss: 318675.85878013197
Epoch: 41
loss: 318712.60306645185
Epoch: 42

 42%|          | 42/100 [00:04<00:05, 10.93it/s]

loss: 318670.2363564781
Epoch: 43
loss: 318714.07578837936
Epoch: 44

 46%|          | 46/100 [00:04<00:05, 10.33it/s]

loss: 318663.9797227961
Epoch: 45
loss: 318665.9597714475
Epoch: 46
loss: 318719.6155709081
Epoch: 47

 48%|          | 48/100 [00:04<00:05, 10.25it/s]

loss: 318710.50055592647
Epoch: 48
loss: 318703.7029941426
Epoch: 49
loss: 318689.7575879158
Epoch: 50
```

```
 52%|          | 52/100 [00:05<00:04, 11.00it/s]

loss: 318663.08396758646
Epoch: 51
loss: 318704.0370069698
Epoch: 52
loss: 318664.0097926287
Epoch: 53

 54%|          | 54/100 [00:05<00:04, 11.01it/s]

loss: 318706.9350582669
Epoch: 54
loss: 318704.0830384418
Epoch: 55
loss: 318655.8485345048
Epoch: 56

 58%|          | 58/100 [00:05<00:03, 10.96it/s]

loss: 318707.09795855766
Epoch: 57
loss: 318662.06534495077
Epoch: 58
loss: 318709.2226362416
Epoch: 59

 60%|          | 60/100 [00:05<00:03, 10.98it/s]

loss: 318703.5133361685
Epoch: 60
loss: 318692.96043400007
Epoch: 61
loss: 318701.8286885093
Epoch: 62

 64%|          | 64/100 [00:06<00:03, 11.13it/s]

loss: 318700.28577831225
Epoch: 63
loss: 318661.4262641044
Epoch: 64
loss: 318659.8696925944
Epoch: 65

 66%|          | 66/100 [00:06<00:03, 10.87it/s]

loss: 318667.9028781849
Epoch: 66
loss: 318708.71487791545
Epoch: 67
loss: 318707.2120160033
Epoch: 68
```

```
 70%|          | 70/100 [00:06<00:02, 10.98it/s]

loss: 318659.58481290535
Epoch: 69
loss: 318668.7002969256
Epoch: 70
loss: 318662.8222948178
Epoch: 71

 72%|          | 72/100 [00:06<00:02, 10.96it/s]

loss: 318717.3599025905
Epoch: 72
loss: 318709.3087880986
Epoch: 73
loss: 318704.09542429383
Epoch: 74

 76%|          | 76/100 [00:07<00:02, 11.19it/s]

loss: 318661.04639167857
Epoch: 75
loss: 318707.6008583484
Epoch: 76
loss: 318695.9251566142
Epoch: 77

 78%|          | 78/100 [00:07<00:01, 11.13it/s]

loss: 318661.36298395006
Epoch: 78
loss: 318664.19054200343
Epoch: 79
loss: 318671.03618320904
Epoch: 80

 82%|          | 82/100 [00:07<00:01, 11.14it/s]

loss: 318673.26254084485
Epoch: 81
loss: 318678.22051800514
Epoch: 82
loss: 318683.9796217147
Epoch: 83

 84%|          | 84/100 [00:07<00:01, 11.08it/s]

loss: 318724.88047655305
Epoch: 84
loss: 318678.51323592087
Epoch: 85
loss: 318678.25516199344
Epoch: 86
```

```
 88%|      | 88/100 [00:08<00:01, 11.47it/s]

loss: 318683.553930789
Epoch: 87
loss: 318686.58413043077
Epoch: 88
loss: 318725.7053599159
Epoch: 89

 90%|      | 90/100 [00:08<00:01,  9.49it/s]

loss: 318716.3445245104
Epoch: 90
loss: 318672.1753786618
Epoch: 91
loss: 318712.5091793149
Epoch: 92

 94%|     | 94/100 [00:08<00:00, 10.47it/s]

loss: 318705.7842817341
Epoch: 93
loss: 318703.3358106956
Epoch: 94
loss: 318702.1161463208
Epoch: 95

 96%|     | 96/100 [00:09<00:00, 10.73it/s]

loss: 318648.37061671156
Epoch: 96
loss: 318705.5051914206
Epoch: 97
loss: 318660.8100649795
Epoch: 98

100%|     | 100/100 [00:09<00:00, 10.62it/s]

loss: 318706.9723564252
Epoch: 99
loss: 318706.056116819
Epoch: 100
loss: 318660.70305448596
```

[ ]:

```
# Evaluating Stochastic Gradient Descent From Scratch
y_hat = lr_model.predict(X_val_scaled)
r2_score(y_val, y_hat)

r2_sgd_scratch = r2_score(y_val, y_hat)
mean_squared_error_sgd_scratch = mean_squared_error(y_val, y_hat)
```

```
mean_squared_error_sgd_scratch
```

[ ]: 371980.47684652015

0.3 Batch Gradient Descent

```
numerical_features_standard = ['BHK_NO.', 'SQUARE_FT', 'LONGITUDE', 'LATITUDE']
numerical_transformer_standard = Pipeline(steps=[
    ('standard_scaler', StandardScaler())
])
```

```
# Combine preprocessing steps
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', categorical_transformer, categorical_features),
        ('num_minmax', numerical_transformer_standard,␣
 ↪numerical_features_standard)
    ],
    remainder='passthrough'
)
```

```
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
```

```
total_training_samples = df_train.shape[0]
total_training_samples
```

[ ]: 29050

```
from sklearn.base import BaseEstimator, RegressorMixin
```

```

```

```
def batches(X, y, chunksize, num_samples):
  start = 0
  while start < num_samples:
    end = min(start + chunksize, num_samples)
    X_chunk, y_chunk = X[start:end], y[start:end]
    yield X_chunk, y_chunk
    start += chunksize
```

```
from sklearn.linear_model import LinearRegression

num_samples = X_train.shape[0]
batch_iterator = batches(X_train_scaled, y_train, num_samples, num_samples)
```

```
model = SGDRegressor(max_iter=100, eta0=0.0001)

for X_chunk, y_chunk in batch_iterator:
  model.partial_fit(X_chunk, y_chunk)
```

[ ]:
```
## Evaluation R2 score
y_pred = model.predict(X_val_scaled)
r2_sgd_batch = r2_score(y_val, y_pred)
root_mean_squared_error_batch = np.sqrt(mean_squared_error(y_val, y_pred))
root_mean_squared_error_batch
```

[ ]: 699.8636789132277

Batch Gradient Descent from Scratch

[ ]:
```
class BatchLinearRegression:
  def __init__(self,
               m: int,
               lr: float=0.01,
               epoch: int=10,
               clip_threshold: int=1):
    self.m = m
    self.lr = lr
    self.epoch = epoch
    self.clip_threshold = clip_threshold


  def initialize_params(self, X):
    # self.weights = np.random.randn(X.shape[1]) * np.sqrt(2/(X.shape[1] + 1))
    self.weights = np.random.randn(X.shape[1]) * 0.001
    self.bias = 0

  def compute_loss(self, X, Y=None):
    Y_hat = X @ self.weights + self.bias
    self.loss = np.sum((Y - Y_hat)**2)/(2*self.m) if Y is not None else None

    return self.loss, Y_hat

  def get_error(self, Y, Y_hat):
    error = Y - Y_hat
    error = error.reshape(Y.shape[0], 1)
    return error

  def update_params(self, X, Y, Y_hat):
    error = self.get_error(Y, Y_hat)
    dW = - (1 / (2 * self.m)) * (X.T @ error)
    dW = dW.reshape(self.weights.shape)
```

```
    dB = - (1 / (2 * self.m)) * np.sum(error)

    self.weights -= self.lr * dW
    self.bias -= self.lr * dB

  def fit(self, X, Y):
    self.initialize_params(X)
    total_loss = 0

    for i in tqdm(range(self.epoch)):
      print(f"Epoch: {i + 1}")
      loss, Y_hat = self.compute_loss(X, Y)
      print(f"Loss: {loss}")
      self.update_params(X, Y, Y_hat)
      # print(f"Updated Weights: {self.weights}")

  def predict(self, X):
    _, Y_hat = self.compute_loss(X)
    return Y_hat
```

[ ]:
```
## Trainig Batch Gradient Descent

lr_model_batch = BatchLinearRegression(X_train_scaled.shape[0], lr=0.001,␣
↪epoch=500, clip_threshold=1)
lr_model_batch.fit(X_train_scaled, y_train)
```

```
  4%|          | 20/500 [00:00<00:02, 186.45it/s]

Epoch: 1
Loss: 205450.68015461025
Epoch: 2
Loss: 205402.21212236377
Epoch: 3
Loss: 205353.79937596552
Epoch: 4
Loss: 205305.4418423017
Epoch: 5
Loss: 205257.13944837597
Epoch: 6
Loss: 205208.8921213091
Epoch: 7
Loss: 205160.69978833882
Epoch: 8
Loss: 205112.5623768197
Epoch: 9
Loss: 205064.47981422264
Epoch: 10
Loss: 205016.45202813484
```

```
Epoch: 11
Loss: 204968.47894625968
Epoch: 12
Loss: 204920.5604964162
Epoch: 13
Loss: 204872.6966065392
Epoch: 14
Loss: 204824.88720467876
Epoch: 15
Loss: 204777.13221900017
Epoch: 16
Loss: 204729.4315777837
Epoch: 17
Loss: 204681.78520942418
Epoch: 18
Loss: 204634.1930424312
Epoch: 19
Loss: 204586.65500542836
Epoch: 20
Loss: 204539.17102715358
Epoch: 21
Loss: 204491.74103645835
Epoch: 22
Loss: 204444.36496230814
Epoch: 23
Loss: 204397.0427337814
Epoch: 24
Loss: 204349.77428007018
Epoch: 25
Loss: 204302.55953047925
Epoch: 26
Loss: 204255.39841442616
Epoch: 27
Loss: 204208.29086144123
Epoch: 28
Loss: 204161.23680116676
Epoch: 29
Loss: 204114.23616335736
Epoch: 30
Loss: 204067.28887787962
Epoch: 31
Loss: 204020.3948747116
Epoch: 32
Loss: 203973.55408394308
Epoch: 33
Loss: 203926.76643577483
Epoch: 34
Loss: 203880.0318605189
```

```
Epoch: 35
Loss: 203833.350288598
Epoch: 36
Loss: 203786.7216505456
Epoch: 37
Loss: 203740.14587700556
Epoch: 38
Loss: 203693.6228987318

 12%|          | 60/500 [00:00<00:02, 192.31it/s]

Epoch: 39
Loss: 203647.15264658834
Epoch: 40
Loss: 203600.73505154907
Epoch: 41
Loss: 203554.3700446973
Epoch: 42
Loss: 203508.05755722572
Epoch: 43
Loss: 203461.79752043626
Epoch: 44
Loss: 203415.58986573984
Epoch: 45
Loss: 203369.43452465587
Epoch: 46
Loss: 203323.33142881253
Epoch: 47
Loss: 203277.28050994626
Epoch: 48
Loss: 203231.2816999016
Epoch: 49
Loss: 203185.334930631
Epoch: 50
Loss: 203139.44013419462
Epoch: 51
Loss: 203093.5972427602
Epoch: 52
Loss: 203047.80618860267
Epoch: 53
Loss: 203002.06690410402
Epoch: 54
Loss: 202956.3793217534
Epoch: 55
Loss: 202910.7433741463
Epoch: 56
Loss: 202865.15899398486
Epoch: 57
Loss: 202819.6261140776
```

```
Epoch: 58
Loss: 202774.14466733896
Epoch: 59
Loss: 202728.71458678934
Epoch: 60
Loss: 202683.33580555482
Epoch: 61
Loss: 202638.00825686686
Epoch: 62
Loss: 202592.7318740624
Epoch: 63
Loss: 202547.50659058325
Epoch: 64
Loss: 202502.33233997622
Epoch: 65
Loss: 202457.20905589277
Epoch: 66
Loss: 202412.1366720889
Epoch: 67
Loss: 202367.1151224248
Epoch: 68
Loss: 202322.14434086476
Epoch: 69
Loss: 202277.22426147707
Epoch: 70
Loss: 202232.35481843367
Epoch: 71
Loss: 202187.53594600977
Epoch: 72
```

```
 23%|          | 117/500 [00:00<00:01, 245.57it/s]
```

```
Loss: 202142.7675785843
Epoch: 73
Loss: 202098.04965063895
Epoch: 74
Loss: 202053.3820967585
Epoch: 75
Loss: 202008.76485163037
Epoch: 76
Loss: 201964.19785004455
Epoch: 77
Loss: 201919.68102689335
Epoch: 78
Loss: 201875.21431717117
Epoch: 79
Loss: 201830.7976559745
Epoch: 80
Loss: 201786.4309785013
```

```
Epoch: 81
Loss: 201742.11422005147
Epoch: 82
Loss: 201697.84731602596
Epoch: 83
Loss: 201653.63020192695
Epoch: 84
Loss: 201609.46281335776
Epoch: 85
Loss: 201565.34508602237
Epoch: 86
Loss: 201521.27695572545
Epoch: 87
Loss: 201477.25835837203
Epoch: 88
Loss: 201433.28922996734
Epoch: 89
Loss: 201389.36950661676
Epoch: 90
Loss: 201345.49912452538
Epoch: 91
Loss: 201301.67801999807
Epoch: 92
Loss: 201257.90612943907
Epoch: 93
Loss: 201214.183389352
Epoch: 94
Loss: 201170.50973633956
Epoch: 95
Loss: 201126.88510710336
Epoch: 96
Loss: 201083.30943844368
Epoch: 97
Loss: 201039.78266725942
Epoch: 98
Loss: 200996.3047305478
Epoch: 99
Loss: 200952.8755654042
Epoch: 100
Loss: 200909.49510902204
Epoch: 101
Loss: 200866.16329869247
Epoch: 102
Loss: 200822.8800718044
Epoch: 103
Loss: 200779.64536584396
Epoch: 104
Loss: 200736.45911839476
```

```
Epoch: 105
Loss: 200693.32126713733
Epoch: 106
Loss: 200650.23174984916
Epoch: 107
Loss: 200607.19050440443
Epoch: 108
Loss: 200564.1974687738
Epoch: 109
Loss: 200521.25258102443
Epoch: 110
Loss: 200478.35577931936
Epoch: 111
Loss: 200435.50700191807
Epoch: 112
Loss: 200392.70618717538
Epoch: 113
Loss: 200349.95327354196
Epoch: 114
Loss: 200307.24819956397
Epoch: 115
Loss: 200264.5909038827
Epoch: 116
Loss: 200221.9813252347
Epoch: 117
Loss: 200179.4194024512
Epoch: 118
Loss: 200136.90507445845
Epoch: 119
Loss: 200094.43828027704
Epoch: 120
Loss: 200052.01895902198
Epoch: 121
Loss: 200009.64704990265
Epoch: 122
Loss: 199967.32249222227
Epoch: 123
Loss: 199925.04522537798
Epoch: 124
Loss: 199882.81518886064
Epoch: 125
Loss: 199840.63232225453
Epoch: 126
Loss: 199798.49656523735
Epoch: 127
Loss: 199756.40785757994
Epoch: 128
Loss: 199714.3661391461
```

```
Epoch: 129
Loss: 199672.3713498924
Epoch: 130
Loss: 199630.42342986807
Epoch: 131
Loss: 199588.52231921494
Epoch: 132
Loss: 199546.66795816692
Epoch: 133
Loss: 199504.86028705022
Epoch: 134
Loss: 199463.0992462828
Epoch: 135
Loss: 199421.38477637467
Epoch: 136
Loss: 199379.71681792723
Epoch: 137
Loss: 199338.0953116334
Epoch: 138
Loss: 199296.5201982774
Epoch: 139
Loss: 199254.99141873434
Epoch: 140
Loss: 199213.5089139706
Epoch: 141
Loss: 199172.07262504302
Epoch: 142
Loss: 199130.6824930993
Epoch: 143
Loss: 199089.33845937724
Epoch: 144
Loss: 199048.04046520518
Epoch: 145
Loss: 199006.78845200143
Epoch: 146
Loss: 198965.58236127425
Epoch: 147
Loss: 198924.42213462153
Epoch: 148
Loss: 198883.30771373093
Epoch: 149
Loss: 198842.23904037953
Epoch: 150
Loss: 198801.21605643345
Epoch: 151
Loss: 198760.23870384804
Epoch: 152
Loss: 198719.3069246677
```

```
Epoch: 153
Loss: 198678.42066102545
Epoch: 154
Loss: 198637.5798551428
Epoch: 155
Loss: 198596.78444932992
Epoch: 156
Loss: 198556.0343859851
Epoch: 157
Loss: 198515.32960759482
Epoch: 158
Loss: 198474.67005673342
Epoch: 159
Loss: 198434.05567606312
Epoch: 160
Loss: 198393.4864083337
Epoch: 161
Loss: 198352.96219638234
Epoch: 162
Loss: 198312.48298313364
Epoch: 163
Loss: 198272.0487115992
Epoch: 164
Loss: 198231.6593248777
Epoch: 165
Loss: 198191.31476615465
Epoch: 166
Loss: 198151.01497870206
Epoch: 167
Loss: 198110.75990587857
Epoch: 168
Loss: 198070.54949112906
Epoch: 169
Loss: 198030.38367798476
Epoch: 170
Loss: 197990.26241006269
Epoch: 171
Loss: 197950.1856310658
Epoch: 172
Loss: 197910.15328478292
Epoch: 173
Loss: 197870.16531508806
Epoch: 174
Loss: 197830.22166594098
Epoch: 175
Loss: 197790.32228138644
Epoch: 176
Loss: 197750.46710555427
```

```
Epoch: 177
Loss: 197710.65608265938
Epoch: 178
Loss: 197670.88915700134
Epoch: 179
Loss: 197631.16627296415
Epoch: 180
Loss: 197591.48737501664
Epoch: 181
Loss: 197551.85240771156
Epoch: 182
Loss: 197512.26131568596
Epoch: 183
Loss: 197472.7140436609
Epoch: 184
Loss: 197433.21053644113
Epoch: 185
Loss: 197393.75073891532
Epoch: 186
Loss: 197354.33459605536
Epoch: 187
Loss: 197314.96205291667
Epoch: 188
Loss: 197275.6330546379
Epoch: 189
Loss: 197236.34754644075
Epoch: 190
Loss: 197197.1054736297
Epoch: 191
Loss: 197157.90678159217
Epoch: 192
Loss: 197118.75141579806
Epoch: 193
Loss: 197079.63932179977
Epoch: 194
Loss: 197040.570445232
Epoch: 195
Loss: 197001.54473181165
Epoch: 196
Loss: 196962.56212733744
Epoch: 197
Loss: 196923.62257769023
Epoch: 198
Loss: 196884.72602883223
Epoch: 199
Loss: 196845.87242680762
Epoch: 200
Loss: 196807.06171774157
```

```
Epoch: 201
Loss: 196768.29384784075
Epoch: 202
Loss: 196729.56876339298
Epoch: 203
Loss: 196690.88641076678
Epoch: 204
Loss: 196652.2467364117
Epoch: 205
Loss: 196613.64968685797
Epoch: 206
Loss: 196575.0952087161
Epoch: 207
Loss: 196536.5832486773
Epoch: 208
Loss: 196498.11375351273
Epoch: 209
Loss: 196459.68667007366
Epoch: 210
Loss: 196421.3019452915
Epoch: 211
Loss: 196382.95952617715
Epoch: 212
Loss: 196344.65935982144
Epoch: 213
Loss: 196306.40139339442
Epoch: 214
Loss: 196268.1855741457
Epoch: 215
Loss: 196230.011849404
Epoch: 216
Loss: 196191.88016657706
Epoch: 217
Loss: 196153.79047315166
Epoch: 218
Loss: 196115.74271669323
Epoch: 219
Loss: 196077.736844846
Epoch: 220
Loss: 196039.7728053324
Epoch: 221
Loss: 196001.85054595346
Epoch: 222
Loss: 195963.97001458838
Epoch: 223
Loss: 195926.13115919428
Epoch: 224
Loss: 195888.33392780635
```

```
Epoch: 225
Loss: 195850.5782685374
Epoch: 226
```

```
 62%|       | 311/500 [00:00<00:00, 541.20it/s]
```

```
Loss: 195812.8641295781
Epoch: 227
Loss: 195775.19145919642
Epoch: 228
Loss: 195737.56020573774
Epoch: 229
Loss: 195699.97031762465
Epoch: 230
Loss: 195662.42174335688
Epoch: 231
Loss: 195624.914431511
Epoch: 232
Loss: 195587.44833074042
Epoch: 233
Loss: 195550.02338977525
Epoch: 234
Loss: 195512.639557422
Epoch: 235
Loss: 195475.29678256367
Epoch: 236
Loss: 195437.99501415947
Epoch: 237
Loss: 195400.7342012447
Epoch: 238
Loss: 195363.5142929306
Epoch: 239
Loss: 195326.33523840428
Epoch: 240
Loss: 195289.19698692852
Epoch: 241
Loss: 195252.0994878417
Epoch: 242
Loss: 195215.04269055757
Epoch: 243
Loss: 195178.02654456513
Epoch: 244
Loss: 195141.0509994286
Epoch: 245
Loss: 195104.11600478718
Epoch: 246
Loss: 195067.22151035487
Epoch: 247
Loss: 195030.36746592054
```

Epoch: 248
Loss: 194993.55382134762
Epoch: 249
Loss: 194956.780526574
Epoch: 250
Loss: 194920.04753161184
Epoch: 251
Loss: 194883.3547865476
Epoch: 252
Loss: 194846.70224154173
Epoch: 253
Loss: 194810.08984682872
Epoch: 254
Loss: 194773.51755271672
Epoch: 255
Loss: 194736.9853095878
Epoch: 256
Loss: 194700.49306789707
Epoch: 257
Loss: 194664.0407781737
Epoch: 258
Loss: 194627.62839101962
Epoch: 259
Loss: 194591.25585711005
Epoch: 260
Loss: 194554.9231271934
Epoch: 261
Loss: 194518.63015209069
Epoch: 262
Loss: 194482.37688269583
Epoch: 263
Loss: 194446.16326997534
Epoch: 264
Loss: 194409.98926496814
Epoch: 265
Loss: 194373.85481878565
Epoch: 266
Loss: 194337.75988261137
Epoch: 267
Loss: 194301.70440770104
Epoch: 268
Loss: 194265.68834538222
Epoch: 269
Loss: 194229.7116470544
Epoch: 270
Loss: 194193.77426418877
Epoch: 271
Loss: 194157.87614832807

Epoch: 272
Loss: 194122.0172510865
Epoch: 273
Loss: 194086.1975241497
Epoch: 274
Loss: 194050.41691927426
Epoch: 275
Loss: 194014.6753882881
Epoch: 276
Loss: 193978.9728830898
Epoch: 277
Loss: 193943.3093556491
Epoch: 278
Loss: 193907.6847580062
Epoch: 279
Loss: 193872.09904227188
Epoch: 280
Loss: 193836.5521606274
Epoch: 281
Loss: 193801.04406532436
Epoch: 282
Loss: 193765.5747086845
Epoch: 283
Loss: 193730.14404309957
Epoch: 284
Loss: 193694.75202103134
Epoch: 285
Loss: 193659.3985950114
Epoch: 286
Loss: 193624.0837176409
Epoch: 287
Loss: 193588.80734159076
Epoch: 288
Loss: 193553.56941960112
Epoch: 289
Loss: 193518.36990448151
Epoch: 290
Loss: 193483.20874911078
Epoch: 291
Loss: 193448.0859064367
Epoch: 292
Loss: 193413.00132947596
Epoch: 293
Loss: 193377.95497131415
Epoch: 294
Loss: 193342.94678510557
Epoch: 295
Loss: 193307.97672407303

```
Epoch: 296
Loss: 193273.04474150794
Epoch: 297
Loss: 193238.15079076975
Epoch: 298
Loss: 193203.29482528646
Epoch: 299
Loss: 193168.47679855392
Epoch: 300
Loss: 193133.69666413614
Epoch: 301
Loss: 193098.95437566476
Epoch: 302
Loss: 193064.24988683924
Epoch: 303
Loss: 193029.58315142675
Epoch: 304
Loss: 192994.95412326188
Epoch: 305
Loss: 192960.36275624647
Epoch: 306
Loss: 192925.8090043498
Epoch: 307
Loss: 192891.29282160813
Epoch: 308
Loss: 192856.8141621249
Epoch: 309
Loss: 192822.37298007018
Epoch: 310
Loss: 192787.9692296811
Epoch: 311
Loss: 192753.60286526123
Epoch: 312
Loss: 192719.2738411808
Epoch: 313
Loss: 192684.98211187636
Epoch: 314
Loss: 192650.7276318509
Epoch: 315
Loss: 192616.51035567347
Epoch: 316
Loss: 192582.3302379792
Epoch: 317
Loss: 192548.18723346922
Epoch: 318
Loss: 192514.08129691047
Epoch: 319
Loss: 192480.01238313568
```

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Epoch: 320
Loss: 192445.98044704297
Epoch: 321
Loss: 192411.98544359618
Epoch: 322
Loss: 192378.02732782447
Epoch: 323
Loss: 192344.1060548221
Epoch: 324
Loss: 192310.22157974867
Epoch: 325
Loss: 192276.37385782858
Epoch: 326
Loss: 192242.56284435152
Epoch: 327
Loss: 192208.78849467152
Epoch: 328
Loss: 192175.05076420758
Epoch: 329
Loss: 192141.34960844315
Epoch: 330
Loss: 192107.68498292626
Epoch: 331
Loss: 192074.05684326915
Epoch: 332
Loss: 192040.46514514825
Epoch: 333
Loss: 192006.90984430432
Epoch: 334
Loss: 191973.39089654194
Epoch: 335
Loss: 191939.90825772955
Epoch: 336
Loss: 191906.46188379952
Epoch: 337
Loss: 191873.05173074777
Epoch: 338
Loss: 191839.67775463386
Epoch: 339
Loss: 191806.3399115806
Epoch: 340
Loss: 191773.03815777446
Epoch: 341
Loss: 191739.7724494648
Epoch: 342
Loss: 191706.5427429643
Epoch: 343
Loss: 191673.3489946485
```

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Epoch: 344
Loss: 191640.19116095584
Epoch: 345
Loss: 191607.06919838776
Epoch: 346
Loss: 191573.98306350803
Epoch: 347
Loss: 191540.93271294318
Epoch: 348
Loss: 191507.9181033821
Epoch: 349
Loss: 191474.93919157612
Epoch: 350
Loss: 191441.99593433875
Epoch: 351
Loss: 191409.08828854552

 86%|      | 428/500 [00:00<00:00, 534.38it/s]

Epoch: 352
Loss: 191376.2162111341
Epoch: 353
Loss: 191343.37965910407
Epoch: 354
Loss: 191310.57858951658
Epoch: 355
Loss: 191277.81295949483
Epoch: 356
Loss: 191245.08272622325
Epoch: 357
Loss: 191212.387846948
Epoch: 358
Loss: 191179.72827897637
Epoch: 359
Loss: 191147.10397967717
Epoch: 360
Loss: 191114.51490648018
Epoch: 361
Loss: 191081.96101687624
Epoch: 362
Loss: 191049.44226841704
Epoch: 363
Loss: 191016.95861871543
Epoch: 364
Loss: 190984.51002544462
Epoch: 365
Loss: 190952.0964463385
Epoch: 366
Loss: 190919.71783919176
```

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Epoch: 367
Loss: 190887.37416185907
Epoch: 368
Loss: 190855.06537225575
Epoch: 369
Loss: 190822.7914283571
Epoch: 370
Loss: 190790.55228819867
Epoch: 371
Loss: 190758.34790987585
Epoch: 372
Loss: 190726.17825154404
Epoch: 373
Loss: 190694.0432714183
Epoch: 374
Loss: 190661.94292777352
Epoch: 375
Loss: 190629.87717894392
Epoch: 376
Loss: 190597.84598332347
Epoch: 377
Loss: 190565.84929936528
Epoch: 378
Loss: 190533.8870855818
Epoch: 379
Loss: 190501.9593005447
Epoch: 380
Loss: 190470.0659028846
Epoch: 381
Loss: 190438.20685129124
Epoch: 382
Loss: 190406.38210451294
Epoch: 383
Loss: 190374.591621357
Epoch: 384
Loss: 190342.8353606893
Epoch: 385
Loss: 190311.11328143417
Epoch: 386
Loss: 190279.4253425746
Epoch: 387
Loss: 190247.7715031517
Epoch: 388
Loss: 190216.15172226485
Epoch: 389
Loss: 190184.56595907183
Epoch: 390
Loss: 190153.0141727881
```

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Epoch: 391
Loss: 190121.49632268722
Epoch: 392
Loss: 190090.01236810078
Epoch: 393
Loss: 190058.56226841768
Epoch: 394
Loss: 190027.14598308483
Epoch: 395
Loss: 189995.7634716065
Epoch: 396
Loss: 189964.41469354456
Epoch: 397
Loss: 189933.09960851804
Epoch: 398
Loss: 189901.8181762033
Epoch: 399
Loss: 189870.5703563338
Epoch: 400
Loss: 189839.3561087001
Epoch: 401
Loss: 189808.1753931497
Epoch: 402
Loss: 189777.028169587
Epoch: 403
Loss: 189745.91439797293
Epoch: 404
Loss: 189714.8340383253
Epoch: 405
Loss: 189683.78705071844
Epoch: 406
Loss: 189652.77339528318
Epoch: 407
Loss: 189621.7930322064
Epoch: 408
Loss: 189590.8459217317
Epoch: 409
Loss: 189559.9320241585
Epoch: 410
Loss: 189529.05129984254
Epoch: 411
Loss: 189498.20370919528
Epoch: 412
Loss: 189467.3892126842
Epoch: 413
Loss: 189436.60777083263
Epoch: 414
Loss: 189405.8593442195
```

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Epoch: 415
Loss: 189375.14389347937
Epoch: 416
Loss: 189344.4613793021
Epoch: 417
Loss: 189313.8117624333
Epoch: 418
Loss: 189283.19500367364
Epoch: 419
Loss: 189252.611063879
Epoch: 420
Loss: 189222.0599039605
Epoch: 421
Loss: 189191.54148488422
Epoch: 422
Loss: 189161.05576767118
Epoch: 423
Loss: 189130.60271339712
Epoch: 424
Loss: 189100.1822831928
Epoch: 425
Loss: 189069.7944382432
Epoch: 426
Loss: 189039.43913978833
Epoch: 427
Loss: 189009.11634912228
Epoch: 428
Loss: 188978.8260275937
Epoch: 429
Loss: 188948.56813660538
Epoch: 430
Loss: 188918.34263761446
Epoch: 431
Loss: 188888.14949213207
Epoch: 432
Loss: 188857.98866172333
Epoch: 433
Loss: 188827.8601080073
Epoch: 434
Loss: 188797.7637926567
Epoch: 435
Loss: 188767.69967739825
Epoch: 436
Loss: 188737.66772401205
Epoch: 437
Loss: 188707.66789433188
Epoch: 438
Loss: 188677.70015024487
```

```
Epoch: 439
Loss: 188647.76445369163
Epoch: 440
Loss: 188617.86076666575
Epoch: 441
Loss: 188587.9890512144
Epoch: 442
Loss: 188558.14926943742
Epoch: 443
Loss: 188528.34138348803
Epoch: 444
Loss: 188498.56535557203
Epoch: 445
Loss: 188468.82114794824
Epoch: 446
Loss: 188439.108722928
Epoch: 447
Loss: 188409.4280428756
```

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100%|      | 500/500 [00:01<00:00, 436.89it/s]
```

```
Epoch: 448
Loss: 188379.77907020747
Epoch: 449
Loss: 188350.1617673928
Epoch: 450
Loss: 188320.57609695298
Epoch: 451
Loss: 188291.0220214618
Epoch: 452
Loss: 188261.49950354514
Epoch: 453
Loss: 188232.00850588095
Epoch: 454
Loss: 188202.5489911993
Epoch: 455
Loss: 188173.1209222821
Epoch: 456
Loss: 188143.72426196313
Epoch: 457
Loss: 188114.35897312794
Epoch: 458
Loss: 188085.02501871355
Epoch: 459
Loss: 188055.72236170885
Epoch: 460
Loss: 188026.45096515398
Epoch: 461
Loss: 187997.21079214054
```

```
Epoch: 462
Loss: 187968.00180581148
Epoch: 463
Loss: 187938.82396936096
Epoch: 464
Loss: 187909.67724603426
Epoch: 465
Loss: 187880.56159912757
Epoch: 466
Loss: 187851.47699198828
Epoch: 467
Loss: 187822.42338801463
Epoch: 468
Loss: 187793.40075065536
Epoch: 469
Loss: 187764.4090434103
Epoch: 470
Loss: 187735.44822982964
Epoch: 471
Loss: 187706.5182735142
Epoch: 472
Loss: 187677.61913811517
Epoch: 473
Loss: 187648.75078733423
Epoch: 474
Loss: 187619.91318492327
Epoch: 475
Loss: 187591.10629468432
Epoch: 476
Loss: 187562.33008046958
Epoch: 477
Loss: 187533.5845061813
Epoch: 478
Loss: 187504.86953577158
Epoch: 479
Loss: 187476.18513324248
Epoch: 480
Loss: 187447.5312626457
Epoch: 481
Loss: 187418.90788808285
Epoch: 482
Loss: 187390.31497370478
Epoch: 483
Loss: 187361.75248371225
Epoch: 484
Loss: 187333.22038235524
Epoch: 485
Loss: 187304.7186339331
```

```
Epoch: 486
Loss: 187276.24720279453
Epoch: 487
Loss: 187247.8060533373
Epoch: 488
Loss: 187219.39515000844
Epoch: 489
Loss: 187191.01445730386
Epoch: 490
Loss: 187162.66393976845
Epoch: 491
Loss: 187134.34356199607
Epoch: 492
Loss: 187106.05328862916
Epoch: 493
Loss: 187077.79308435906
Epoch: 494
Loss: 187049.5629139255
Epoch: 495
Loss: 187021.362742117
Epoch: 496
Loss: 186993.19253377037
Epoch: 497
Loss: 186965.05225377076
Epoch: 498
Loss: 186936.94186705165
Epoch: 499
Loss: 186908.8613385948
Epoch: 500
Loss: 186880.81063343014
```

[ ]:
```python
# Evaluating Batch Gradient Descent from scratch

y_hat_batch = lr_model_batch.predict(X_val_scaled)
r2_sgd_batch_scratch = r2_score(y_val, y_hat_batch)
root_mean_squared_error_batch_scratch = np.sqrt(mean_squared_error(y_val,␣
 ↪y_hat_batch))
root_mean_squared_error_batch_scratch
```

[ ]: 707.5444128533871

[ ]:
```python
results_dict = {
    'SGD scikit-learn': r2_sgd_linear,
    'SGD Scratch': r2_sgd_scratch,
    'Batch scikit-learn': r2_sgd_batch,
    'Batch Scratch': r2_sgd_batch_scratch
```

```
}
```

```
[ ]: summary = pd.DataFrame(list(results_dict.items()), columns=['Method', 'R2␣
     ↪Score'])
```

```
[ ]: summary
```

[ ]:

	Method	R2 Score
0	SGD scikit-learn	0.308877
1	SGD Scratch	0.320667
2	Batch scikit-learn	0.105481
3	Batch Scratch	0.085739

Here, looks like SGD from scratch has better performance than others with the R2 of 0.32

`Stochastic Gradient Descent` (SGD) calculates the gradient using a single training example at each step, resulting in noisier gradient updates. These updates are quicker because they use just one training example, allowing for faster parameter adjustments and potentially faster convergence.

`Batch Gradient Descent`, on the other hand, uses the entire training dataset to compute the gradient. This method can be computationally intensive and slow, particularly with large datasets, but it provides a more accurate direction for parameter updates.