```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

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In [2]:
        def compute_cost(X, y, theta):
            m = len(y)
            predictions = X @ theta
            error = predictions - y
            return (1 / (2 * m)) * np.sum(error ** 2)
        def compute cost l2(X, y, theta, lmbd):
            m = len(y)
            predictions = X @ theta
            error = predictions - y
            theta no bias = theta[1:]
            l2_{term} = (lmbd / (2 * m)) * np.sum(theta_no_bias ** 2)
            return (1 / (2 * m)) * np.sum(error ** 2) + l2 term
        def gradient descent(X train, y train, X val, y val, theta, alpha, it
            m = len(y_train)
            train cost history = []
            val_cost_history = []
            for _ in range(iterations):
                predictions = X_train @ theta
                error = predictions - y_train
                gradient = (1 / m) * (X_train.T @ error)
                theta -= alpha * gradient
                train_cost_history.append(compute_cost(X_train, y_train, thet
                val_cost_history.append(compute_cost(X_val, y_val, theta))
            return theta, train_cost_history, val_cost_history
        def gradient_descent_l2(X_train, y_train, X_val, y_val, theta, alpha)
            m = len(y_train)
            train_cost_history = []
            val_cost_history = []
            for _ in range(iterations):
                predictions = X_train @ theta
                error = predictions - y_train
                gradient = (1 / m) * (X_train.T @ error)
                gradient[1:] += (lmbd / m) * theta[1:] # Regularize all but
                theta -= alpha * gradient
                train cost history.append(compute cost l2(X train, y train, 1
                val_cost_history.append(compute_cost(X_val, y_val, theta))
            return theta, train_cost_history, val_cost_history
        def preprocess binary(values, true word, false word):
            return np.array([1 if val == true_word else 0 for val in values])
        def add bias(X):
            return np.hstack([np.ones((X.shape[0], 1)), X])
        def normalize_train_val(X_train, X_val):
            X_{\min} = X_{\text{train.min}}(axis=0)
            X_{max} = X_{train.max}(axis=0)
            return (X_train - X_min) / (X_max - X_min + 1e-8), (X_val - X min
        def standardize_train_val(X_train, X_val):
```

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X_mean = X_train.mean(axis=0)
X_std = X_train.std(axis=0)
return (X_train - X_mean) / (X_std + 1e-8), (X_val - X_mean) / ()

def train_val_split(X, y, seed=42, train_ratio=0.8):
    np.random.seed(seed)
    indices = np.arange(X.shape[0])
    np.random.shuffle(indices)
    split = int(train_ratio * len(indices))
    train_idx, val_idx = indices[:split], indices[split:]
    return X[train_idx], y[train_idx], X[val_idx], y[val_idx]
```

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In [3]:
        def run_training(X_raw, y, alpha_list, iterations=300, scaling=None,
            X_train, y_train, X_val, y_val = train_val_split(X_raw, y)
            if scaling == 'normalize':
                X train, X val = normalize train val(X train, X val)
            elif scaling == 'standardize':
                X_train, X_val = standardize_train_val(X_train, X_val)
            X_train = add_bias(X_train)
            X_{val} = add_bias(X_{val})
            best val loss = float('inf')
            best theta = None
            best_alpha = None
            plt.figure()
            for alpha in alpha list:
                theta = np.zeros(X_train.shape[1])
                if use 12:
                     theta, train_loss, val_loss = gradient_descent_l2(X_train
                else:
                     theta, train_loss, val_loss = gradient_descent(X_train, )
                plt.plot(train loss, label=f'Train \alpha={alpha}')
                plt.plot(val_loss, label=f'Val \alpha={alpha}', linestyle='--')
                if val_loss[-1] < best_val_loss:</pre>
                     best_val_loss = val_loss[-1]
                     best theta = theta
                     best alpha = alpha
            plt.xlabel('Iterations')
            plt.ylabel('Loss')
            plt.title(title + f" | {'L2' if use_l2 else 'No Reg'} | Scaling:
            plt.legend()
            plt.grid(True)
            plt.show()
            print("Best alpha:", best_alpha)
            print("Best validation loss:", best_val_loss)
            print("Best theta:", best theta)
            print("=" * 50)
```

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In [4]:
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```
df = pd.read csv("Housing.csv")
price = df.values[:, 0].astype(float)
area = df.values[:, 1].astype(float)
bedrooms = df.values[:, 2].astype(float)
bathrooms = df.values[:, 3].astype(float)
stories = df.values[:, 4].astype(float)
mainroad = preprocess_binary(df.values[:, 5], 'yes', 'no')
guestroom = preprocess_binary(df.values[:, 6], 'yes', 'no')
basement = preprocess_binary(df.values[:, 7], 'yes', 'no')
hotwaterheating = preprocess binary(df.values[:, 8], 'yes',
airconditioning = preprocess binary(df.values[:, 9], 'yes',
parking = df.values[:, 10].astype(float)
prefarea = preprocess_binary(df.values[:, 11], 'yes', 'no')
furnishing_map = {'furnished': 2, 'semi-furnished': 1, 'unfurnished':
furnishingstatus = np.array([furnishing map[val] for val in df.values
X_5feat = np.column_stack([area, bedrooms, bathrooms, stories, parkir
X 11feat = np.column stack([
    area, bedrooms, bathrooms, stories, mainroad, guestroom,
    basement, hotwaterheating, airconditioning, parking, prefarea
1)
Y = price
```

```
In [5]:
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run_training(X_5feat, Y, alpha_list=[0.01, 0.005, 0.001], scaling=Nor
```

/tmp/ipykernel\_50469/3460745883.py:5: RuntimeWarning: overflow enco untered in square

return (1 / (2 \* m)) \* np.sum(error \*\* 2)

/tmp/ipykernel\_50469/3460745883.py:24: RuntimeWarning: overflow enc ountered in matmul

gradient = (1 / m) \* (X\_train.T @ error)

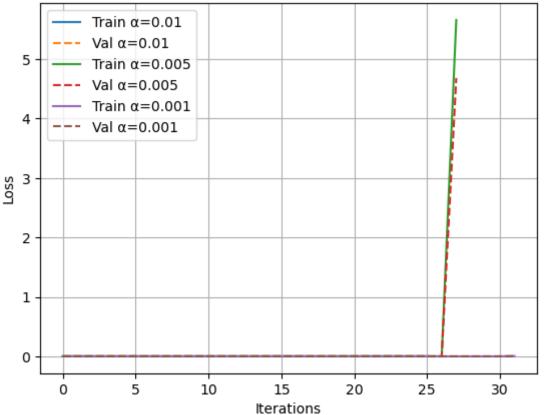
/tmp/ipykernel\_50469/3460745883.py:24: RuntimeWarning: invalid valu
e encountered in matmul

gradient = (1 / m) \* (X\_train.T @ error)

/tmp/ipykernel\_50469/3460745883.py:25: RuntimeWarning: invalid valu
e encountered in subtract

theta -= alpha \* gradient





Best alpha: None

Best validation loss: inf

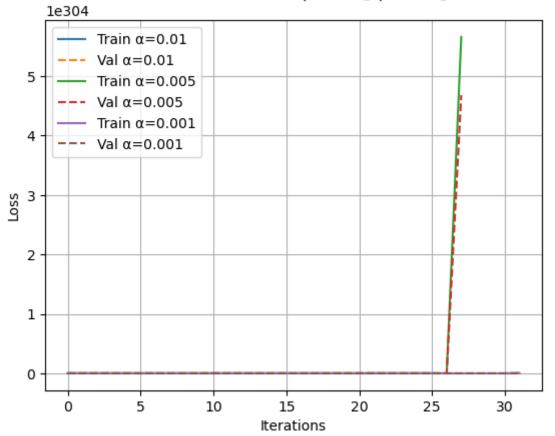
Best theta: None

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In [6]: run_training(X_11feat, Y, alpha_list=[0.01, 0.005, 0.001], scaling=No
```

```
/tmp/ipykernel_50469/3460745883.py:5: RuntimeWarning: overflow enco
untered in square
  return (1 / (2 * m)) * np.sum(error ** 2)
/tmp/ipykernel_50469/3460745883.py:24: RuntimeWarning: overflow enc
ountered in matmul
  gradient = (1 / m) * (X_train.T @ error)
/tmp/ipykernel_50469/3460745883.py:24: RuntimeWarning: invalid valu
e encountered in matmul
  gradient = (1 / m) * (X_train.T @ error)
/tmp/ipykernel_50469/3460745883.py:25: RuntimeWarning: invalid valu
e encountered in subtract
  theta -= alpha * gradient
```

Problem 1.b - 11 features | No Reg | Scaling: None



Best alpha: None

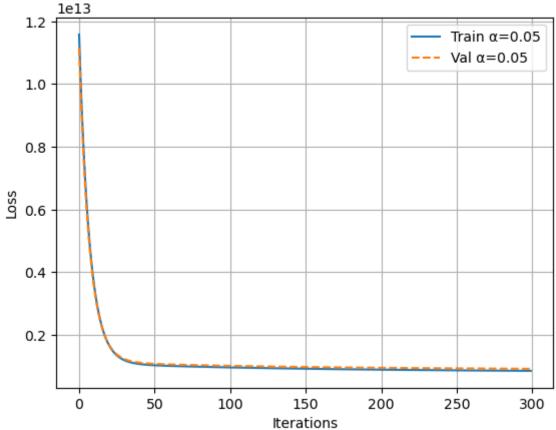
Best validation loss: inf

Best theta: None

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In [7]: run\_training(X\_5feat, Y, alpha\_list=[0.05], scaling='normalize', use\_

Problem 2.a - Normalize | No Reg | Scaling: normalize



Best alpha: 0.05

Best validation loss: 914789510001.5039

Best theta: [2741525.00376411 1894561.72333687 1393377.22078436 175

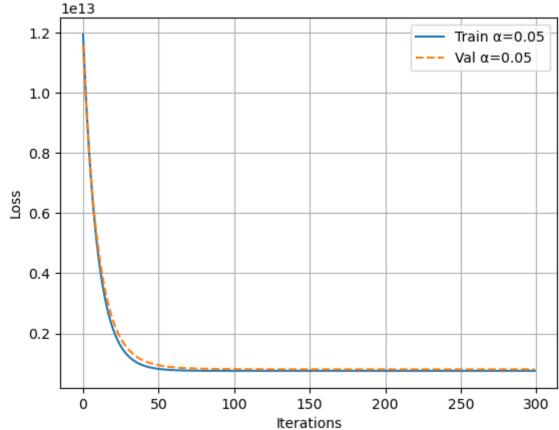
2704.85454135

1647842.57831107 1440884.63789266]

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In [8]: run\_training(X\_5feat, Y, alpha\_list=[0.05], scaling='standardize', us





Best alpha: 0.05

Best validation loss: 809659397828.79

Best theta: [4788864.6942385 708603.47602057 129574.5089913 56

7906.06238621

521644.1502452 316306.47695305]

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