# Fahad_st125981_ML_assignment_3

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### 0.0.1 A3: Predicting Car Price

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### 0.0.2 Github Repository Link

https://github.com/mfahadwaqar/st125981_ML_A3

[37]:
```python
# Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import warnings
warnings.filterwarnings("ignore")
```

[38]:
```python
# Loading Data
df = pd.read_csv("Cars.csv")    # Reading data from the csv file
print(df.head())
```

```
                          name  year  selling_price  km_driven    fuel  \
0       Maruti Swift Dzire VDI  2014         450000     145500  Diesel
1  Skoda Rapid 1.5 TDI Ambition  2014         370000     120000  Diesel
2      Honda City 2017-2020 EXi  2006         158000     140000  Petrol
3     Hyundai i20 Sportz Diesel  2010         225000     127000  Diesel
4        Maruti Swift VXI BSIII  2007         130000     120000  Petrol

  seller_type transmission         owner     mileage   engine   max_power  \
0  Individual       Manual   First Owner   23.4 kmpl  1248 CC      74 bhp
1  Individual       Manual  Second Owner  21.14 kmpl  1498 CC  103.52 bhp
2  Individual       Manual   Third Owner   17.7 kmpl  1497 CC      78 bhp
3  Individual       Manual   First Owner   23.0 kmpl  1396 CC      90 bhp
4  Individual       Manual   First Owner   16.1 kmpl  1298 CC    88.2 bhp

                     torque  seats
```

```
0            190Nm@ 2000rpm    5.0
1       250Nm@ 1500-2500rpm    5.0
2      12.7@ 2,700(kgm@ rpm)    5.0
3   22.4 kgm at 1750-2750rpm    5.0
4      11.5@ 4,500(kgm@ rpm)    5.0
```

[39]:
```python
# EDA
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8128 entries, 0 to 8127
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   name           8128 non-null   object
 1   year           8128 non-null   int64
 2   selling_price  8128 non-null   int64
 3   km_driven      8128 non-null   int64
 4   fuel           8128 non-null   object
 5   seller_type    8128 non-null   object
 6   transmission   8128 non-null   object
 7   owner          8128 non-null   object
 8   mileage        7907 non-null   object
 9   engine         7907 non-null   object
 10  max_power      7913 non-null   object
 11  torque         7906 non-null   object
 12  seats          7907 non-null   float64
dtypes: float64(1), int64(3), object(9)
memory usage: 825.6+ KB
```

[40]:
```python
df.shape    # Shape of the dataset
```

[40]: (8128, 13)

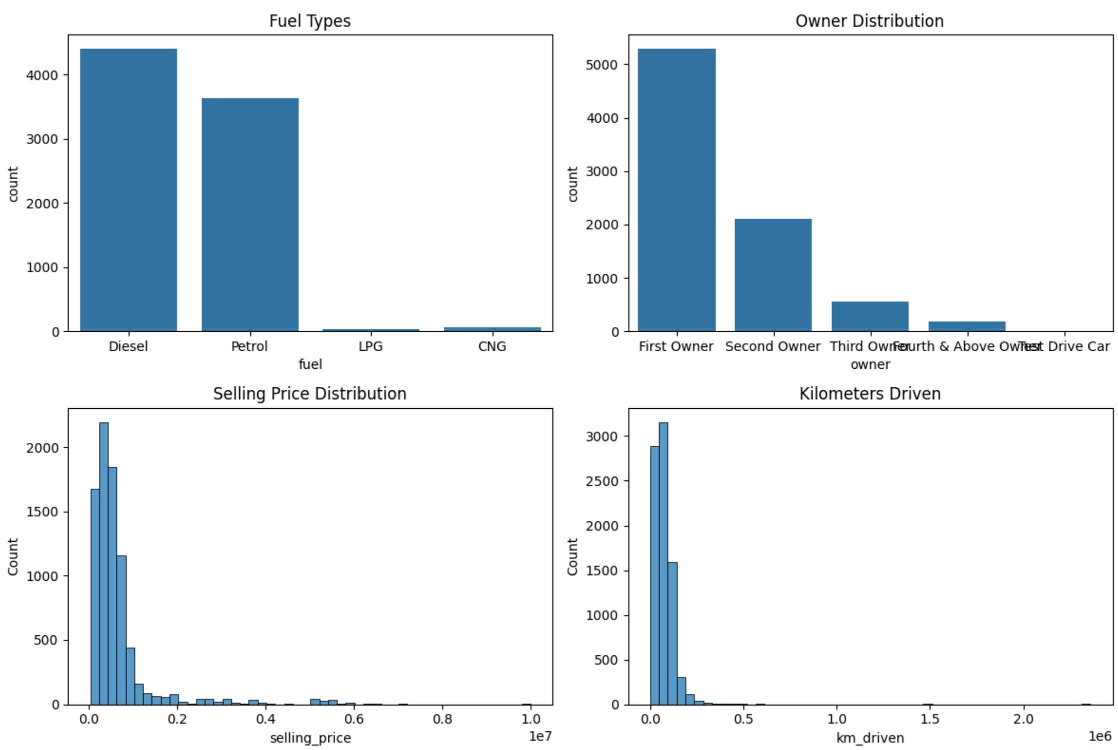
[41]:
```python
print(df.describe())  # Statistical summary of the dataset
```

```
              year  selling_price     km_driven        seats
count  8128.000000   8.128000e+03  8.128000e+03  7907.000000
mean   2013.804011   6.382718e+05  6.981951e+04     5.416719
std       4.044249   8.062534e+05  5.655055e+04     0.959588
min    1983.000000   2.999900e+04  1.000000e+00     2.000000
25%    2011.000000   2.549990e+05  3.500000e+04     5.000000
50%    2015.000000   4.500000e+05  6.000000e+04     5.000000
75%    2017.000000   6.750000e+05  9.800000e+04     5.000000
max    2020.000000   1.000000e+07  2.360457e+06    14.000000
```

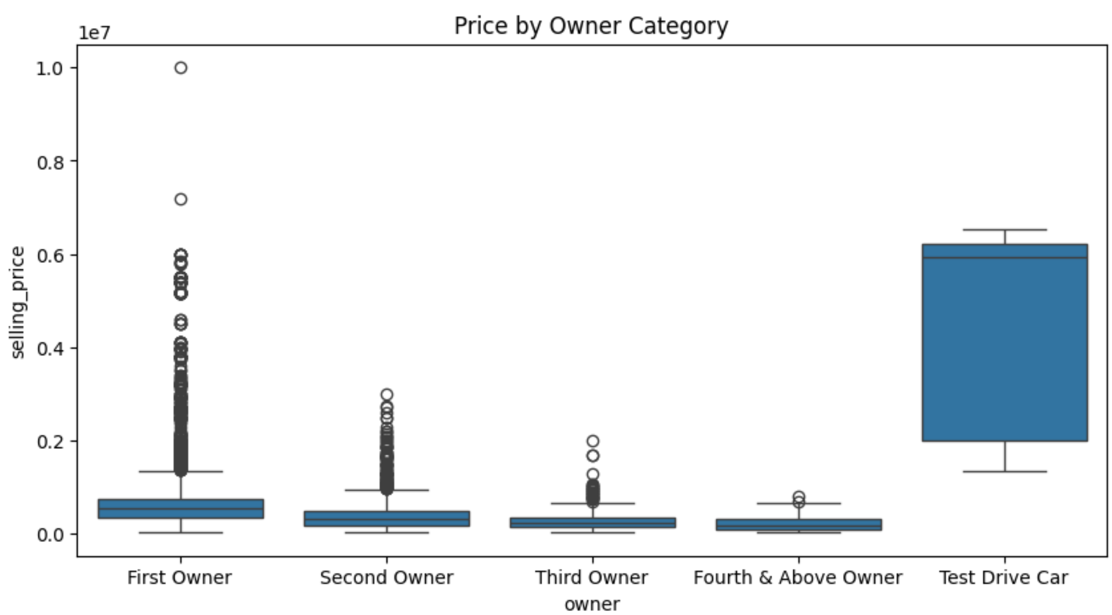
[42]:
```python
# Checking missing values in each column
df.isnull().sum()
```

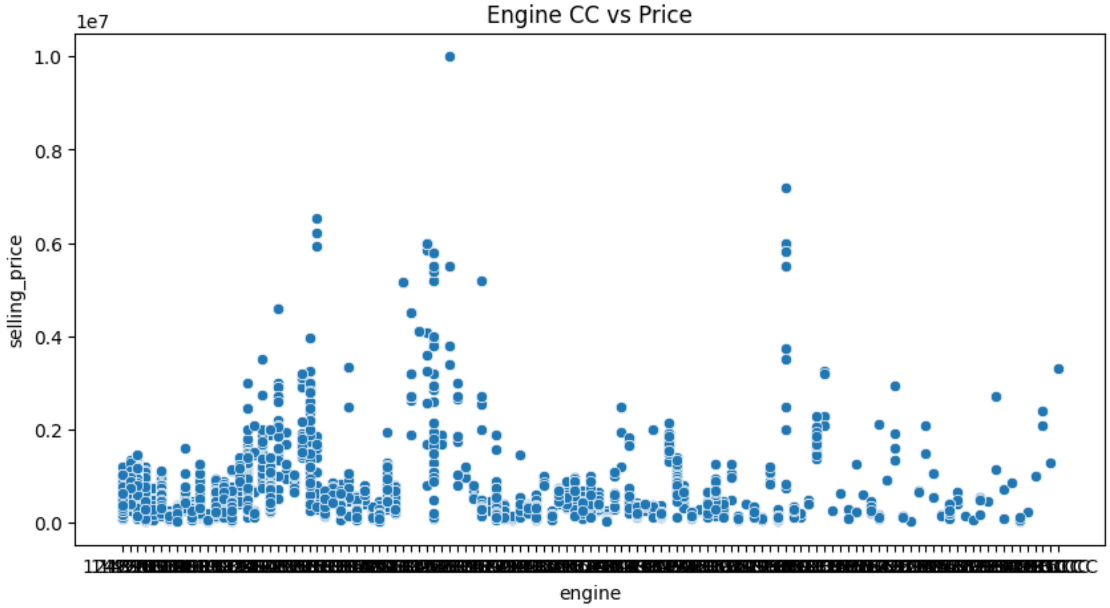
[42]:
```
name                0
year                0
selling_price       0
km_driven           0
fuel                0
seller_type         0
transmission        0
owner               0
mileage           221
engine            221
max_power         215
torque            222
seats             221
dtype: int64
```

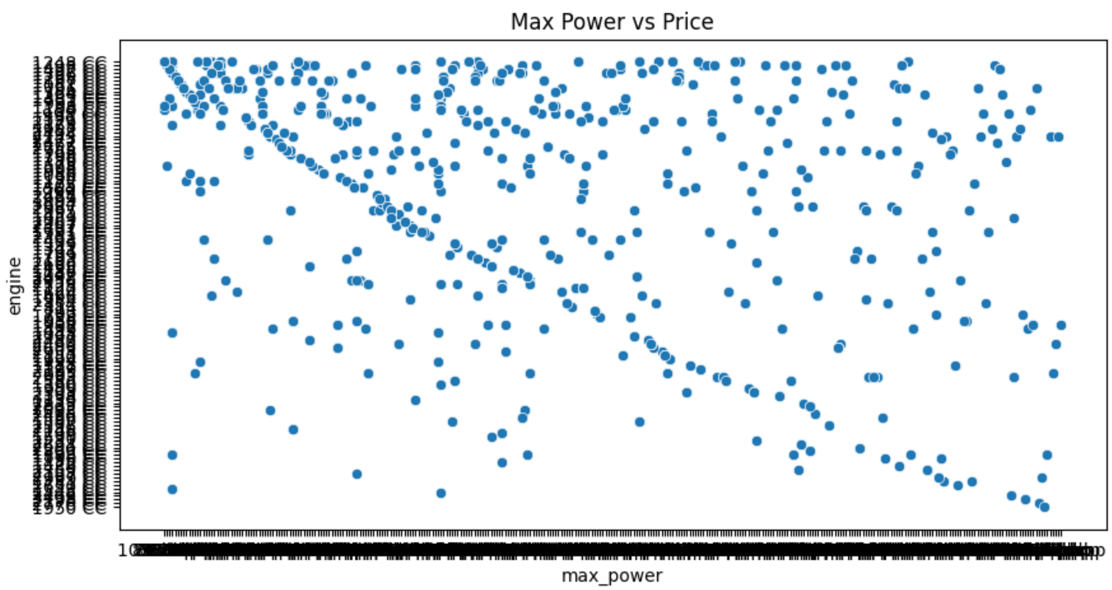
[43]:
```python
# Univariate Analysis
fig, axes = plt.subplots(2, 2, figsize=(12, 8))
sns.countplot(x="fuel", data=df, ax=axes[0,0]).set_title("Fuel Types")
sns.countplot(x="owner", data=df, ax=axes[0,1]).set_title("Owner Distribution")
sns.histplot(df["selling_price"], bins=50, ax=axes[1,0]).set_title("Selling␣
↪Price Distribution")
sns.histplot(df["km_driven"], bins=50, ax=axes[1,1]).set_title("Kilometers␣
↪Driven")
plt.tight_layout()
```

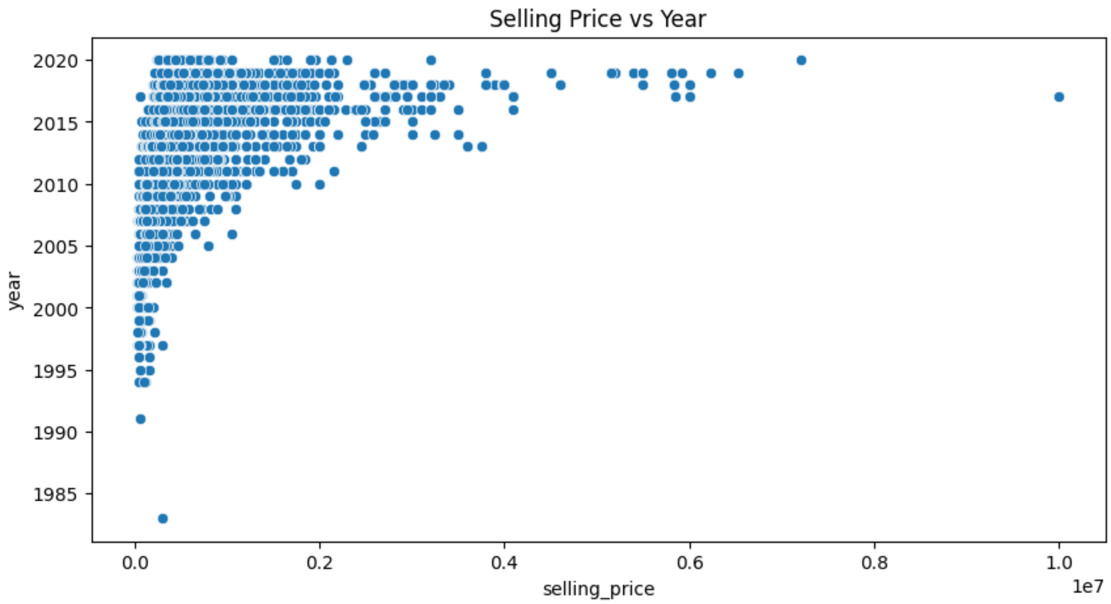


[44]:
```python
# Multivariate Analysis
plt.figure(figsize=(10, 5))
sns.boxplot(x="owner", y="selling_price", data=df).set_title("Price by Owner␣
↪Category")
plt.show()

plt.figure(figsize=(10, 5))
sns.scatterplot(x="engine", y="selling_price", data=df).set_title("Engine CC vs␣
↪Price")
plt.show()

plt.figure(figsize=(10, 5))
sns.scatterplot(x="max_power", y="engine", data=df).set_title("Max Power vs␣
↪Price")
plt.show()

plt.figure(figsize=(10, 5))
sns.scatterplot(x="selling_price", y="year", data=df).set_title("Selling Price␣
↪vs Year")
plt.show()
```



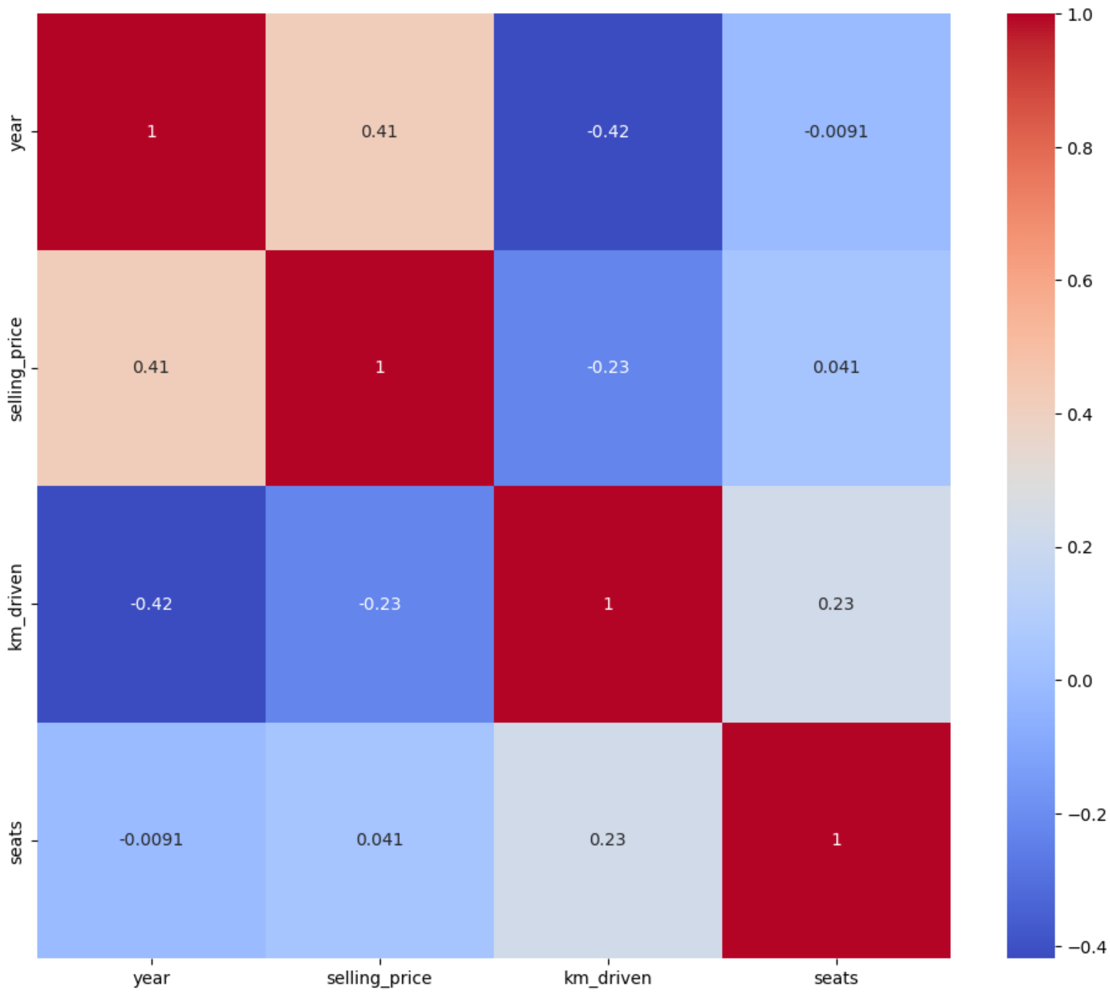

Engine CC vs Price
1e7
1.0
0.8
0.6
0.4
0.2
0.0
selling_price
engine


Max Power vs Price
engine
max_power



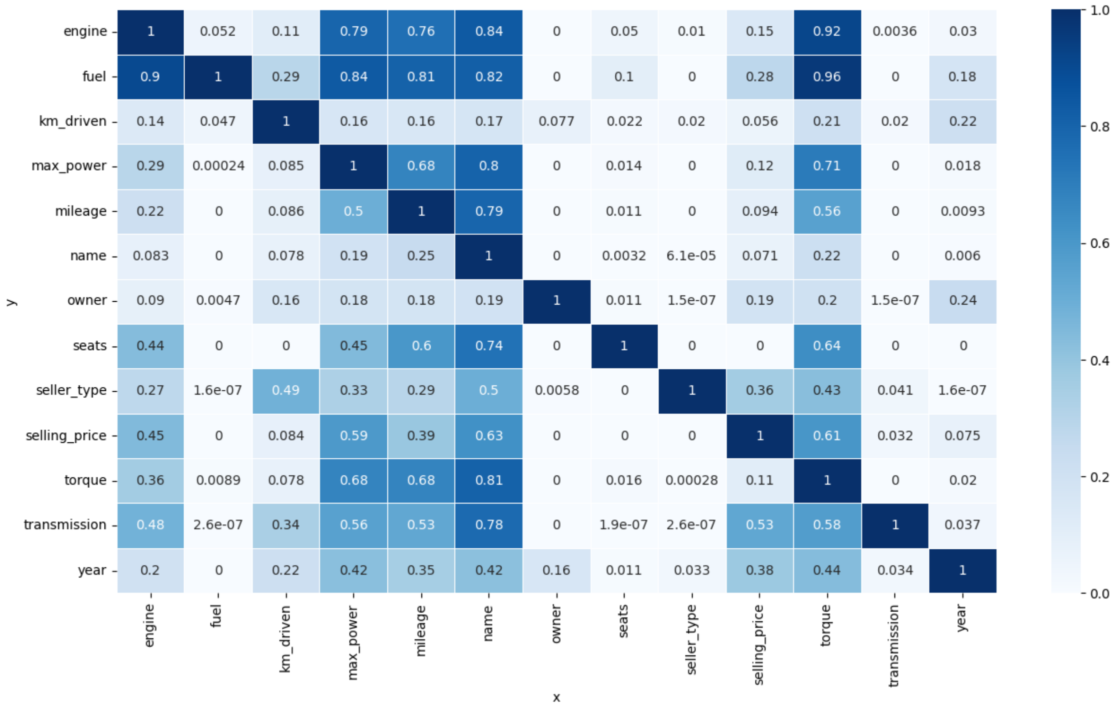

[45]:
```
plt.figure(figsize=(12, 10))
sns.heatmap(df.select_dtypes(include='number').corr(), annot=True,␣
↪cmap='coolwarm')
```

[45]: <Axes: >




[46]:
```python
import ppscore as pps

matrix_df = pps.matrix(df)[['x', 'y', 'ppscore']].pivot(columns='x', index='y',␣
↪values='ppscore')

#plot
plt.figure(figsize=(15, 8))
sns.heatmap(matrix_df, vmin=0, vmax=1, cmap="Blues", linewidths=0.5, annot=True)
```

[46]: <Axes: xlabel='x', ylabel='y'>




[47]:
```python
# Feature Selection
# Creating a function for data cleaning and feature engineering to be used␣
↪after data splitting
def clean_data(df):
    df = df.copy()

    # Drop torque column
    if "torque" in df.columns:
        df.drop(columns="torque", inplace=True)

    # Remove CNG and LPG
    df = df[~df["fuel"].isin(["CNG", "LPG"])]

    # Remove Test Drive Car from owner
    df = df[df["owner"] != "Test Drive Car"]

    # Convert mileage, engine, max_power to numeric
    df["mileage"] = df["mileage"].str.extract(r'(\d+\.?\d*)').astype(float)
    df["engine"] = df["engine"].str.extract(r'(\d+\.?\d*)').astype(float)
    df["max_power"] = df["max_power"].str.extract(r'(\d+\.?\d*)').astype(float)

    # Extract brand name
    if "name" in df.columns:
        df["brand"] = df["name"].str.split(" ").str[0]
```

```
    # Map owner to numeric
    owner_mapping = {
        "First Owner": 1,
        "Second Owner": 2,
        "Third Owner": 3,
        "Fourth & Above Owner": 4
    }
    df["owner"] = df["owner"].map(owner_mapping)

    return df
```

[48]:
```
# Splitting into train and test sets
train_df, test_df = train_test_split(df, test_size=0.1, random_state=42)

# Applying the cleaning function to both splits
train_df_clean = clean_data(train_df)
test_df_clean = clean_data(test_df)

# Seperating features and targets
X_train = train_df_clean[["year", "km_driven", "mileage", "engine",␣
↪"max_power", "transmission", "owner", "brand"]]
y_train = np.log(train_df_clean["selling_price"])

X_test = test_df_clean[["year", "km_driven", "mileage", "engine", "max_power",␣
↪"transmission", "owner", "brand"]]
y_test = np.log(test_df_clean["selling_price"])

print("Train shape:", X_train.shape, "Test shape:", X_test.shape)
```

```
Train shape: (7229, 8) Test shape: (799, 8)
```

[49]:
```
# Preprocessing
# Rearranging columns
cols = X_train.columns.tolist()
cols.insert(0, cols.pop(cols.index('brand')))
X_train = X_train[cols]
```

[50]:
```
cols = X_test.columns.tolist()
cols.insert(0, cols.pop(cols.index('brand')))
X_test = X_test[cols]
```

[51]:
```
print(X_train.head())
```

```
         brand  year  km_driven  mileage  engine  max_power transmission  \
7287  Mahindra  2019      17000    17.30  1497.0      121.0       Manual
3027    Maruti  2016     120000    26.59  1248.0       74.0       Manual
2941    Maruti  2012     100000    19.10  1197.0       85.8       Manual
```

```
4269       BMW  2019       7500     16.78  1995.0       190.0    Automatic
3182  Mahindra  2017      88754     16.00  2179.0       140.0       Manual

      owner
7287      1
3027      3
2941      1
4269      1
3182      1
```

[52]:

```python
numeric_features = ["year", "km_driven", "mileage", "engine", "max_power"]
categorical_features = ["brand", "transmission", "owner"]

# Split data into numeric and categorical subsets
X_train_num = X_train[numeric_features].copy()
X_test_num  = X_test[numeric_features].copy()

X_train_cat = X_train[categorical_features].copy()
X_test_cat  = X_test[categorical_features].copy()

# Imputation and Scaling for numeric features
num_medians = X_train_num.median()
X_train_num = X_train_num.fillna(num_medians)
X_test_num  = X_test_num.fillna(num_medians)

scaler = StandardScaler()
X_train_num_scaled = pd.DataFrame(
    scaler.fit_transform(X_train_num),
    columns=numeric_features,
    index=X_train.index
)
X_test_num_scaled = pd.DataFrame(
    scaler.transform(X_test_num),
    columns=numeric_features,
    index=X_test.index
)

# Imputation and Encoding for categorical features
cat_modes = X_train_cat.mode().iloc[0]
X_train_cat = X_train_cat.fillna(cat_modes)
X_test_cat  = X_test_cat.fillna(cat_modes)

encode = OneHotEncoder(drop="first", sparse_output=False,␣
 ↪handle_unknown="ignore")
X_train_cat_ohe = pd.DataFrame(
    encode.fit_transform(X_train_cat),
    columns=encode.get_feature_names_out(categorical_features),
```

```
    index=X_train.index
)
X_test_cat_ohe = pd.DataFrame(
    encode.transform(X_test_cat),
    columns=encode.get_feature_names_out(categorical_features),
    index=X_test.index
)

# Putting the processed data back together
X_train = pd.concat([X_train_num_scaled, X_train_cat_ohe], axis=1)
X_test  = pd.concat([X_test_num_scaled,  X_test_cat_ohe],  axis=1)

print("Processed train shape:", X_train.shape)
print("Processed test  shape:", X_test.shape)
```

```
Processed train shape: (7229, 40)
Processed test  shape: (799, 40)
```

## 0.1 Task 1: Classification & Task 2: Ridge Logistic Regression

[53]:

```
# Converting selling_price to 4 discrtete classes

# Converting selling_price back from log space to original prices for binning
train_prices_original = np.exp(y_train)
test_prices_original = np.exp(y_test)

# Making 4 bins for classification
bins = pd.qcut(train_prices_original, q=4, labels=[0, 1, 2, 3],␣
 ↪duplicates='drop')
y_train_class = bins.astype(int)

# Applying the same to test set
bin_edges = pd.qcut(train_prices_original, q=4, duplicates='drop',␣
 ↪retbins=True)[1]
y_test_class = pd.cut(test_prices_original, bins=bin_edges, labels=[0, 1, 2,␣
 ↪3], include_lowest=True).astype(int)

print(f"Class distribution in training set:")
print(y_train_class.value_counts().sort_index())
print(f"\nClass distribution in test set:")
print(y_test_class.value_counts().sort_index())
```

```
Class distribution in training set:
selling_price
0    1849
1    1841
2    1743
3    1796
```

```
Name: count, dtype: int64

Class distribution in test set:
selling_price
0    201
1    203
2    200
3    195
Name: count, dtype: int64
```

[54]:

```python
# Multinomial Logistic Regression Implemetation
class LogisticRegression:
    def __init__(self, learning_rate=0.01, max_iterations=1000,
 ↪regularization=None, lambda_reg=0.01):
        self.learning_rate = learning_rate
        self.max_iterations = max_iterations
        self.regularization = regularization
        self.lambda_reg = lambda_reg
        self.W = None
        self.losses = []

    def softmax(self, theta_t_x):
        theta_t_x = np.array(theta_t_x)
        exp_vals = np.exp(theta_t_x - np.max(theta_t_x, axis=1, keepdims=True))
        return exp_vals / np.sum(exp_vals, axis=1, keepdims=True)

    def h_theta(self, X, W):
        X = np.array(X)   # ← Added this line
        return self.softmax(X @ W)

    def gradient(self, X, Y):
        m = X.shape[0]
        h = self.h_theta(X, self.W)

        # Cross-entropy loss
        loss = -np.sum(Y * np.log(h + 1e-8)) / m

        if self.regularization == 'ridge':
            loss += self.lambda_reg * np.sum(self.W ** 2) / (2 * m)

        # Compute gradient
        error = h - Y
        grad = X.T @ error / m

        if self.regularization == 'ridge':
            grad += self.lambda_reg * self.W / m
```

```
        return loss, grad

    def fit(self, X, y):
        X = np.array(X)
        y = np.array(y)

        # Get dimensions
        m, n = X.shape
        k = len(np.unique(y))  # number of classes

        # Initialize weights
        self.W = np.random.normal(0, 0.01, (n, k))

        # Convert y to one-hot encoding
        Y_encoded = np.zeros((m, k))
        for i, label in enumerate(y):
            Y_encoded[i, label] = 1

        # Training loop
        self.losses = []
        for i in range(self.max_iterations):
            loss, grad = self.gradient(X, Y_encoded)
            self.losses.append(loss)
            self.W = self.W - self.learning_rate * grad

            if i % 100 == 0:
                print(f"Loss at iteration {i}: {loss}")

    def predict(self, X):
        X = np.array(X)
        return np.argmax(self.h_theta(X, self.W), axis=1)

    def predict_proba(self, X):
        X = np.array(X)
        return self.h_theta(X, self.W)

    def plot_losses(self):
        plt.figure(figsize=(10, 6))
        plt.plot(self.losses)
        plt.title('Training Loss Over Iterations')
        plt.xlabel('Iteration')
        plt.ylabel('Cross-Entropy Loss')
        plt.grid(True)
        plt.show()
```

[55]:
```
# Evaluation Metrics
class ClassificationMetrics:
```

```python
    def __init__(self, y_true, y_pred, classes=None):
        self.y_true = np.array(y_true)
        self.y_pred = np.array(y_pred)
        self.classes = classes if classes is not None else np.unique(np.concatenate([y_true, y_pred]))
        self.n_classes = len(self.classes)
        self._compute_confusion_matrix()

    def _compute_confusion_matrix(self):
        self.confusion_matrix = np.zeros((self.n_classes, self.n_classes), dtype=int)
        for i, true_class in enumerate(self.classes):
            for j, pred_class in enumerate(self.classes):
                self.confusion_matrix[i, j] = np.sum((self.y_true == true_class) & (self.y_pred == pred_class))

    def accuracy(self):
        correct_predictions = np.sum(self.y_true == self.y_pred)
        total_predictions = len(self.y_true)
        return correct_predictions / total_predictions

    def precision(self, class_idx=None):
        if class_idx is not None:
            tp = self.confusion_matrix[class_idx, class_idx]
            fp = np.sum(self.confusion_matrix[:, class_idx]) - tp
            return tp / (tp + fp) if (tp + fp) > 0 else 0.0
        else:
            precisions = []
            for i in range(self.n_classes):
                precisions.append(self.precision(i))
            return np.array(precisions)

    def recall(self, class_idx=None):
        if class_idx is not None:
            tp = self.confusion_matrix[class_idx, class_idx]
            fn = np.sum(self.confusion_matrix[class_idx, :]) - tp
            return tp / (tp + fn) if (tp + fn) > 0 else 0.0
        else:
            recalls = []
            for i in range(self.n_classes):
                recalls.append(self.recall(i))
            return np.array(recalls)

    def f1_score(self, class_idx=None):
        if class_idx is not None:
            prec = self.precision(class_idx)
            rec = self.recall(class_idx)
```

```
            return 2 * (prec * rec) / (prec + rec) if (prec + rec) > 0 else 0.0
        else:
            f1_scores = []
            for i in range(self.n_classes):
                f1_scores.append(self.f1_score(i))
            return np.array(f1_scores)

    def macro_precision(self):
        precisions = self.precision()
        return np.mean(precisions)

    def macro_recall(self):
        recalls = self.recall()
        return np.mean(recalls)

    def macro_f1(self):
        f1_scores = self.f1_score()
        return np.mean(f1_scores)

    def weighted_precision(self):
        precisions = self.precision()
        support = [np.sum(self.y_true == class_label) for class_label in self.
↪classes]
        total_support = np.sum(support)
        weights = [s / total_support for s in support]
        return np.sum([w * p for w, p in zip(weights, precisions)])

    def weighted_recall(self):
        recalls = self.recall()
        support = [np.sum(self.y_true == class_label) for class_label in self.
↪classes]
        total_support = np.sum(support)
        weights = [s / total_support for s in support]
        return np.sum([w * r for w, r in zip(weights, recalls)])

    def weighted_f1(self):
        f1_scores = self.f1_score()
        support = [np.sum(self.y_true == class_label) for class_label in self.
↪classes]
        total_support = np.sum(support)
        weights = [s / total_support for s in support]
        return np.sum([w * f for w, f in zip(weights, f1_scores)])

    def classification_report(self):
        support = [np.sum(self.y_true == class_label) for class_label in self.
↪classes]
```

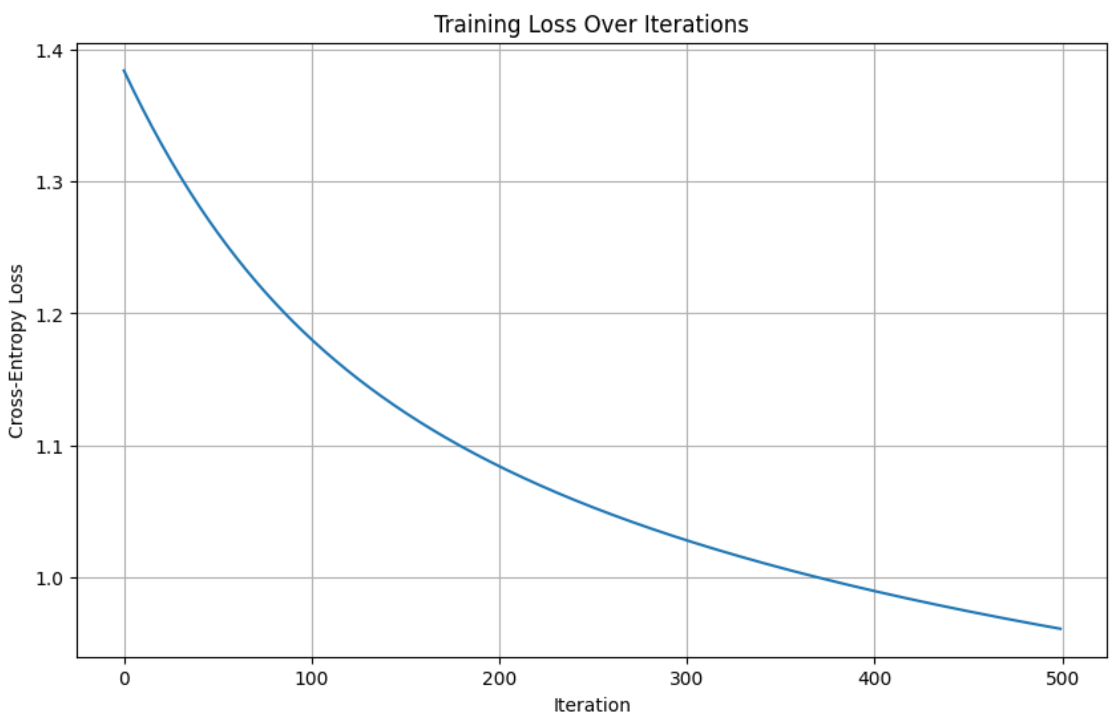
```
        print(f"{'Class':<10} {'Precision':<10} {'Recall':<10} {'F1-Score':<10}␣
↪{'Support':<10}")
        print("-" * 50)

        precisions = self.precision()
        recalls = self.recall()
        f1_scores = self.f1_score()

        for i, class_label in enumerate(self.classes):
            print(f"{class_label:<10} {precisions[i]:<10.3f} {recalls[i]:<10.
↪3f} {f1_scores[i]:<10.3f} {support[i]:<10}")

        print("-" * 50)
        print(f"{'Accuracy':<10} {'':<10} {'':<10} {self.accuracy():<10.3f} {np.
↪sum(support):<10}")
        print(f"{'Macro Avg':<10} {self.macro_precision():<10.3f} {self.
↪macro_recall():<10.3f} {self.macro_f1():<10.3f} {np.sum(support):<10}")
        print(f"{'Weighted Avg':<10} {self.weighted_precision():<10.3f} {self.
↪weighted_recall():<10.3f} {self.weighted_f1():<10.3f} {np.sum(support):<10}")
```

[56]:

```
# Testing Implementation
# Training custom model
print("Training custom Logistic Regression...")
custom_model = LogisticRegression(learning_rate=0.01, max_iterations=500)
custom_model.fit(X_train, y_train_class)

# Make predictions
y_pred_custom = custom_model.predict(X_test)

# Evaluate with custom metrics
print("Custom Implementation Results")
custom_metrics = ClassificationMetrics(y_test_class, y_pred_custom)
custom_metrics.classification_report()

# Plot training loss
custom_model.plot_losses()

# Compare with sklearn
from sklearn.linear_model import LogisticRegression as SklearnLogisticRegression
from sklearn.metrics import classification_report

print("Comparing with sklearn")
sklearn_model = SklearnLogisticRegression(multi_class='multinomial',␣
↪solver='lbfgs', max_iter=500)
sklearn_model.fit(X_train, y_train_class)
y_pred_sklearn = sklearn_model.predict(X_test)
```

```python
print("Sklearn Classification Report:")
print(classification_report(y_test_class, y_pred_sklearn))
```

```
Training custom Logistic Regression…
Loss at iteration 0: 1.3840307045241076
Loss at iteration 100: 1.1802860057536837
Loss at iteration 200: 1.084184448588857
Loss at iteration 300: 1.028002722695251
Loss at iteration 400: 0.9896152504095714
Custom Implementation Results
Class      Precision  Recall     F1-Score   Support
--------------------------------------------------
0          0.651      0.935      0.767      201
1          0.557      0.335      0.418      203
2          0.485      0.415      0.447      200
3          0.659      0.733      0.694      195
--------------------------------------------------
Accuracy                         0.603      799
Macro Avg  0.588      0.605      0.582      799
Weighted Avg 0.588      0.603      0.581      799
```




```
Comparing with sklearn
Sklearn Classification Report:
              precision    recall  f1-score   support
```

```
           0       0.85      0.84      0.85       201
           1       0.61      0.60      0.60       203
           2       0.55      0.62      0.58       200
           3       0.83      0.75      0.79       195

    accuracy                           0.70       799
   macro avg       0.71      0.70      0.70       799
weighted avg       0.71      0.70      0.70       799
```

[57]:
```python
# Ridge Logistic Regression Test
print("Ridge Logistic Regression Test")

# Train with Ridge regularization
ridge_model = LogisticRegression(learning_rate=0.01, max_iterations=500,
                                 regularization='ridge', lambda_reg=0.1)
ridge_model.fit(X_train, y_train_class)
y_pred_ridge = ridge_model.predict(X_test)

ridge_metrics = ClassificationMetrics(y_test_class, y_pred_ridge)
print("Ridge Regularized Results:")
ridge_metrics.classification_report()
```

```
Ridge Logistic Regression Test
Loss at iteration 0: 1.390120576275421
Loss at iteration 100: 1.1840401718231859
Loss at iteration 200: 1.086821503984475
Loss at iteration 300: 1.0300346672984226
Loss at iteration 400: 0.9912695053227906
Ridge Regularized Results:
Class      Precision  Recall     F1-Score   Support
--------------------------------------------------
0          0.651      0.935      0.767      201
1          0.558      0.355      0.434      203
2          0.482      0.400      0.437      200
3          0.656      0.723      0.688      195
--------------------------------------------------
Accuracy                         0.602      799
Macro Avg  0.587      0.603      0.582      799
Weighted Avg 0.586      0.602      0.581      799
```

## 0.2 Task 3: Deployment

[58]:
```python
# MLFlow Experiment Logging
import mlflow
import mlflow.sklearn
from sklearn.model_selection import cross_val_score
import pickle
```

```
import os
```

[61]:
```
# Setup MLflow tracking with authentication
mlflow.set_tracking_uri("http://mlflow.ml.brain.cs.ait.ac.th/")

# Set authentication credentials (from A2 instructions: username='admin',␣
↪password='password')
os.environ['MLFLOW_TRACKING_USERNAME'] = 'admin'
os.environ['MLFLOW_TRACKING_PASSWORD'] = 'password'

mlflow.set_experiment("st125981-a3")  # Replace st125981 with your student ID

def log_model_experiment(model, model_name, X_train, X_test, y_train, y_test,␣
↪params):
    with mlflow.start_run(run_name=model_name):
        # Log parameters
        for key, value in params.items():
            mlflow.log_param(key, value)

        # Log the trained model (so it can be registered later)
        mlflow.sklearn.log_model(model, artifact_path="model")

        # Make predictions
        y_pred = model.predict(X_test)

        # Calculate metrics using your custom implementation
        metrics_calc = ClassificationMetrics(y_test, y_pred)

        # Log all metrics to MLflow
        mlflow.log_metric("accuracy", metrics_calc.accuracy())
        mlflow.log_metric("macro_precision", metrics_calc.macro_precision())
        mlflow.log_metric("macro_recall", metrics_calc.macro_recall())
        mlflow.log_metric("macro_f1", metrics_calc.macro_f1())
        mlflow.log_metric("weighted_precision", metrics_calc.
↪weighted_precision())
        mlflow.log_metric("weighted_recall", metrics_calc.weighted_recall())
        mlflow.log_metric("weighted_f1", metrics_calc.weighted_f1())

        # Log per-class metrics
        precisions = metrics_calc.precision()
        recalls = metrics_calc.recall()
        f1_scores = metrics_calc.f1_score()

        for i, class_label in enumerate(metrics_calc.classes):
            mlflow.log_metric(f"precision_class_{class_label}", precisions[i])
            mlflow.log_metric(f"recall_class_{class_label}", recalls[i])
            mlflow.log_metric(f"f1_class_{class_label}", f1_scores[i])
```

```
        print(f"Logged {model_name} - Run ID: {mlflow.active_run().info.
 ↪run_id}")
        return mlflow.active_run().info.run_id
```

[ ]:

```
# Experiment 1: Basic Logistic Regression
print("Experiment 1: Basic Logistic Regression")
basic_model = LogisticRegression(learning_rate=0.01, max_iterations=500,␣
 ↪regularization=None)
basic_model.fit(X_train, y_train_class)

basic_params = {
    "model_type": "LogisticRegression",
    "learning_rate": 0.01,
    "max_iterations": 500,
    "regularization": "none",
    "lambda_reg": 0.0
}

basic_run_id = log_model_experiment(
    basic_model, "basic_logistic_regression",
    X_train, X_test, y_train_class, y_test_class,
    basic_params
)

# Experiment 2: Ridge Logistic Regression
print("\nExperiment 2: Ridge Logistic Regression")
ridge_model = LogisticRegression(learning_rate=0.01, max_iterations=500,
                                regularization='ridge', lambda_reg=0.1)
ridge_model.fit(X_train, y_train_class)

ridge_params = {
    "model_type": "LogisticRegression",
    "learning_rate": 0.01,
    "max_iterations": 500,
    "regularization": "ridge",
    "lambda_reg": 0.1
}

ridge_run_id = log_model_experiment(
    ridge_model, "ridge_logistic_regression",
    X_train, X_test, y_train_class, y_test_class,
    ridge_params
)

# Experiment 3: Different Learning Rates
print("\nExperiment 3: Testing Different Learning Rates")
```

```python
learning_rates = [0.001, 0.01, 0.1]

for lr in learning_rates:
    print(f"Testing learning_rate={lr}")

    temp_model = LogisticRegression(learning_rate=lr, max_iterations=500)
    temp_model.fit(X_train, y_train_class)

    temp_params = {
        "model_type": "LogisticRegression",
        "learning_rate": lr,
        "max_iterations": 500,
        "regularization": "none",
        "lambda_reg": 0.0
    }

    log_model_experiment(
        temp_model, f"logistic_regression_lr_{lr}",
        X_train, X_test, y_train_class, y_test_class,
        temp_params
    )

# Experiment 4: Different Regularization Strengths
print("\nExperiment 4: Testing Different Regularization Strengths")
lambda_values = [0.01, 0.1, 1.0]

for lam in lambda_values:
    print(f"Testing lambda={lam}")

    temp_model = LogisticRegression(learning_rate=0.01, max_iterations=500,
                                   regularization='ridge', lambda_reg=lam)
    temp_model.fit(X_train, y_train_class)

    temp_params = {
        "model_type": "LogisticRegression",
        "learning_rate": 0.01,
        "max_iterations": 500,
        "regularization": "ridge",
        "lambda_reg": lam
    }

    log_model_experiment(
        temp_model, f"ridge_logistic_regression_lambda_{lam}",
        X_train, X_test, y_train_class, y_test_class,
        temp_params
    )
```

```python
# Experiment 5: Different Max Iterations
print("\nExperiment 5: Testing Different Max Iterations")
max_iterations = [100, 500, 1000]

for max_iter in max_iterations:
    print(f"Testing max_iterations={max_iter}")

    temp_model = LogisticRegression(learning_rate=0.01, max_iterations=max_iter)
    temp_model.fit(X_train, y_train_class)

    temp_params = {
        "model_type": "LogisticRegression",
        "learning_rate": 0.01,
        "max_iterations": max_iter,
        "regularization": "none",
        "lambda_reg": 0.0
    }

    log_model_experiment(
        temp_model, f"logistic_regression_maxiter_{max_iter}",
        X_train, X_test, y_train_class, y_test_class,
        temp_params
    )

print(f"View results at: http://mlflow.ml.brain.cs.ait.ac.th/")
print(f"Experiment name: st125981-a3")

print("Finding and registering best model...")

# Get all runs from the experiment
experiment = mlflow.get_experiment_by_name("st125981-a3")
runs = mlflow.search_runs(experiment_ids=[experiment.experiment_id])

# Find the best run based on weighted_f1 score
best_run = runs.loc[runs['metrics.weighted_f1'].idxmax()]
best_run_id = best_run['run_id']
best_weighted_f1 = best_run['metrics.weighted_f1']

print(f"\nBest model found:")
print(f"  Run ID: {best_run_id}")
print(f"  Run Name: {best_run['tags.mlflow.runName']}")
print(f"  Weighted F1: {best_weighted_f1:.4f}")
print(f"  Accuracy: {best_run['metrics.accuracy']:.4f}")

from mlflow import MlflowClient

client = MlflowClient()
```

```python
model_name = "st125981_best_logistic_regression"

# Register the best model from its run ID
model_uri = f"runs:/{best_run_id}/model"

# Register a new version
model_version = mlflow.register_model(model_uri=model_uri, name=model_name)

# Wait for the registration to complete (optional)
import time
time.sleep(5)

# Assign or update the alias (e.g., "Staging")
client.set_registered_model_alias(model_name, "Staging", model_version.version)

print(f"\nBest model registered successfully!")
print(f"Model Name: {model_name}")
print(f"Model Version: {model_version.version}")
print(f"Alias: Staging")
print(f"MLflow URL: http://mlflow.ml.brain.cs.ait.ac.th/#/models/{model_name}")
```

```
Experiment 1: Basic Logistic Regression
Loss at iteration 0: 1.3952661230561991
Loss at iteration 100: 1.1855473260017506
Loss at iteration 200: 1.0869718985599426
Loss at iteration 300: 1.0296683778895568
Loss at iteration 400: 0.990682469274693

2025/10/04 17:35:54 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:35:59 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:35:59 WARNING mlflow.models.model: Model logged without a
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged basic_logistic_regression - Run ID: 5b1fecb19ac0473d9d10773e5a9ab000
 View run basic_logistic_regression at: http://mlflow.ml.brain.cs.ait.ac.th/#/e
xperiments/403651241041143407/runs/5b1fecb19ac0473d9d10773e5a9ab000
 View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407

Experiment 2: Ridge Logistic Regression
Loss at iteration 0: 1.384708515079588
Loss at iteration 100: 1.1821779835479942
Loss at iteration 200: 1.0862831863873634
Loss at iteration 300: 1.0299207655820624
Loss at iteration 400: 0.9912919301327046
```

```
2025/10/04 17:36:13 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:36:15 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:36:15 WARNING mlflow.models.model: Model logged without a
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged ridge_logistic_regression - Run ID: 6fd556ffe509429ca77adc4cd351e8c5
  View run ridge_logistic_regression at: http://mlflow.ml.brain.cs.ait.ac.th/#/e
xperiments/403651241041143407/runs/6fd556ffe509429ca77adc4cd351e8c5
  View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407

Experiment 3: Testing Different Learning Rates
Testing learning_rate=0.001
Loss at iteration 0: 1.387765267225824
Loss at iteration 100: 1.3586839106171098
Loss at iteration 200: 1.3320109304683263
Loss at iteration 300: 1.3075514267319492
Loss at iteration 400: 1.2851135089502983

2025/10/04 17:36:29 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:36:32 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:36:32 WARNING mlflow.models.model: Model logged without a
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged logistic_regression_lr_0.001 - Run ID: 288b90b814544ede935c8ea0aa48d995
  View run logistic_regression_lr_0.001 at: http://mlflow.ml.brain.cs.ait.ac.th/
#/experiments/403651241041143407/runs/288b90b814544ede935c8ea0aa48d995
  View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407
Testing learning_rate=0.01
Loss at iteration 0: 1.3831223081282826
Loss at iteration 100: 1.181550377466806
Loss at iteration 200: 1.0857468433247324
Loss at iteration 300: 1.0294293709979594
Loss at iteration 400: 0.9908511114753946

2025/10/04 17:36:46 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:36:49 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:36:49 WARNING mlflow.models.model: Model logged without a
```

```
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged logistic_regression_lr_0.01 - Run ID: aabd2778112c426f9807fcb0ac2ca137
 View run logistic_regression_lr_0.01 at: http://mlflow.ml.brain.cs.ait.ac.th/#
/experiments/403651241041143407/runs/aabd2778112c426f9807fcb0ac2ca137
 View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407
Testing learning_rate=0.1
Loss at iteration 0: 1.3907288677231786
Loss at iteration 100: 0.8769298044003523
Loss at iteration 200: 0.8040785011532885
Loss at iteration 300: 0.7675581357690282
Loss at iteration 400: 0.7445452161245624

2025/10/04 17:37:03 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:37:06 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:37:06 WARNING mlflow.models.model: Model logged without a
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged logistic_regression_lr_0.1 - Run ID: 6fb48e66e798477083264e84b5977dc2
 View run logistic_regression_lr_0.1 at: http://mlflow.ml.brain.cs.ait.ac.th/#/
experiments/403651241041143407/runs/6fb48e66e798477083264e84b5977dc2
 View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407


Experiment 4: Testing Different Regularization Strengths
Testing lambda=0.01
Loss at iteration 0: 1.3857680409497024
Loss at iteration 100: 1.1821036186803537
Loss at iteration 200: 1.0858147696811016
Loss at iteration 300: 1.0293042852391872
Loss at iteration 400: 0.9906041614557589

2025/10/04 17:37:20 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:37:23 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:37:23 WARNING mlflow.models.model: Model logged without a
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged ridge_logistic_regression_lambda_0.01 - Run ID:
e2b82cae170a44778d6463b802122d2b
 View run ridge_logistic_regression_lambda_0.01 at: http://mlflow.ml.brain.cs.a
```

```
it.ac.th/#/experiments/403651241041143407/runs/e2b82cae170a44778d6463b802122d2b
 View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407
Testing lambda=0.1
Loss at iteration 0: 1.3909243915430425
Loss at iteration 100: 1.183914052452798
Loss at iteration 200: 1.0862729793372345
Loss at iteration 300: 1.0292647632172647
Loss at iteration 400: 0.9903813120476955

2025/10/04 17:37:37 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:37:40 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:37:40 WARNING mlflow.models.model: Model logged without a
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged ridge_logistic_regression_lambda_0.1 - Run ID:
2204452fb2ee487fb63b5c1e16b7adb1
 View run ridge_logistic_regression_lambda_0.1 at: http://mlflow.ml.brain.cs.ai
t.ac.th/#/experiments/403651241041143407/runs/2204452fb2ee487fb63b5c1e16b7adb1
 View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407
Testing lambda=1.0
Loss at iteration 0: 1.3832970067721662
Loss at iteration 100: 1.1804134197537357
Loss at iteration 200: 1.0845309351269128
Loss at iteration 300: 1.0283833767481942
Loss at iteration 400: 0.989993338102195

2025/10/04 17:37:54 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:37:57 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:37:57 WARNING mlflow.models.model: Model logged without a
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged ridge_logistic_regression_lambda_1.0 - Run ID:
a06280067883484b8896b7cfd7447845
 View run ridge_logistic_regression_lambda_1.0 at: http://mlflow.ml.brain.cs.ai
t.ac.th/#/experiments/403651241041143407/runs/a06280067883484b8896b7cfd7447845
 View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407

Experiment 5: Testing Different Max Iterations
Testing max_iterations=100
```

```
Loss at iteration 0: 1.3851654098852488

2025/10/04 17:38:11 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:38:14 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:38:14 WARNING mlflow.models.model: Model logged without a
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged logistic_regression_maxiter_100 - Run ID:
277626cc3b9042f69112c8a1b6490bfc
 View run logistic_regression_maxiter_100 at: http://mlflow.ml.brain.cs.ait.ac.
th/#/experiments/403651241041143407/runs/277626cc3b9042f69112c8a1b6490bfc
 View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407
Testing max_iterations=500
Loss at iteration 0: 1.3821592825259754
Loss at iteration 100: 1.1800206556650719
Loss at iteration 200: 1.084317934469051
Loss at iteration 300: 1.0281748793083316
Loss at iteration 400: 0.9897495453439152

2025/10/04 17:38:28 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:38:31 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:38:31 WARNING mlflow.models.model: Model logged without a
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged logistic_regression_maxiter_500 - Run ID:
194fa30302324f9295ee23e55f69776f
 View run logistic_regression_maxiter_500 at: http://mlflow.ml.brain.cs.ait.ac.
th/#/experiments/403651241041143407/runs/194fa30302324f9295ee23e55f69776f
 View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407
Testing max_iterations=1000
Loss at iteration 0: 1.3872384610129262
Loss at iteration 100: 1.1826853920718026
Loss at iteration 200: 1.0861152579836295
Loss at iteration 300: 1.0295173104317563
Loss at iteration 400: 0.9908016339187147
Loss at iteration 500: 0.9617365013726558
Loss at iteration 600: 0.9386394212600057
Loss at iteration 700: 0.9195930783655573
Loss at iteration 800: 0.9034759555442992
Loss at iteration 900: 0.8895733603072701
```

```
2025/10/04 17:38:47 WARNING mlflow.models.model: `artifact_path` is deprecated.
Please use `name` instead.
2025/10/04 17:38:50 WARNING mlflow.utils.environment: Failed to resolve
installed pip version. ``pip`` will be added to conda.yaml environment spec
without a version specifier.
2025/10/04 17:38:50 WARNING mlflow.models.model: Model logged without a
signature and input example. Please set `input_example` parameter when logging
the model to auto infer the model signature.

Logged logistic_regression_maxiter_1000 - Run ID:
3e85b36d1cfe48c789dbbde28bf42e93
 View run logistic_regression_maxiter_1000 at: http://mlflow.ml.brain.cs.ait.ac
.th/#/experiments/403651241041143407/runs/3e85b36d1cfe48c789dbbde28bf42e93
 View experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/403651241041143407
View results at: http://mlflow.ml.brain.cs.ait.ac.th/
Experiment name: st125981-a3
Finding and registering best model…

Best model found:
  Run ID: 6fb48e66e798477083264e84b5977dc2
  Run Name: logistic_regression_lr_0.1
  Weighted F1: 0.6502
  Accuracy: 0.6521

Registered model 'st125981_best_logistic_regression' already exists. Creating a
new version of this model…
2025/10/04 17:39:04 WARNING mlflow.tracking._model_registry.fluent: Run with id
6fb48e66e798477083264e84b5977dc2 has no artifacts at artifact path 'model',
registering model based on models:/m-ec45281410224c00876c8d6c516b6cfe instead
2025/10/04 17:39:04 INFO mlflow.store.model_registry.abstract_store: Waiting up
to 300 seconds for model version to finish creation. Model name:
st125981_best_logistic_regression, version 1
Created version '1' of model 'st125981_best_logistic_regression'.


Best model registered successfully!
Model Name: st125981_best_logistic_regression
Model Version: 1
Alias: Staging
MLflow URL:
http://mlflow.ml.brain.cs.ait.ac.th/#/models/st125981_best_logistic_regression
```