Experiment No 1

Part A: The Google Colab Code

Python

```
# --- IMPORTS ---
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import fetch_california_housing, load_breast_cancer
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, Ridge, LogisticRegression
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score, classification_report,
confusion_matrix

# ==========================================
# EXPERIMENT 1.1: LINEAR REGRESSION
# Dataset: California Housing
# ==========================================
print("--- STARTING EXPERIMENT 1.1: LINEAR REGRESSION ---")

# 1. Load Data
housing = fetch_california_housing()
X_reg = pd.DataFrame(housing.data, columns=housing.feature_names)
y_reg = housing.target

# 2. Preprocessing
# Split 80/20
X_train_reg, X_test_reg, y_train_reg, y_test_reg = train_test_split(X_reg, y_reg, test_size=0.2,
random_state=42)

# Scaling (Important for regression performance and tuning)
scaler_reg = StandardScaler()
X_train_reg_scaled = scaler_reg.fit_transform(X_train_reg)
X_test_reg_scaled = scaler_reg.transform(X_test_reg)

# 3. Model Training (Standard OLS)
lin_reg = LinearRegression()
lin_reg.fit(X_train_reg_scaled, y_train_reg)
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# 4. Evaluation
y_pred_reg = lin_reg.predict(X_test_reg_scaled)
mse = mean_squared_error(y_test_reg, y_pred_reg)
r2 = r2_score(y_test_reg, y_pred_reg)

print(f"Linear Regression MSE: {mse:.4f}")
print(f"Linear Regression R2 Score: {r2:.4f}")

# 5. Hyperparameter Tuning (Using Ridge Regression as OLS has no hyperparameters to tune)
print("\nPerforming Hyperparameter Tuning (Ridge Regression)...")
ridge = Ridge()
param_grid_reg = {'alpha': [0.1, 1.0, 10.0, 100.0]}
grid_reg = GridSearchCV(ridge, param_grid_reg, cv=5, scoring='r2')
grid_reg.fit(X_train_reg_scaled, y_train_reg)

print(f"Best Alpha for Ridge: {grid_reg.best_params_}")
print(f"Best R2 Score (Ridge): {grid_reg.best_score_:.4f}")
print("-" * 50)


# ==============================================
# EXPERIMENT 1.2: LOGISTIC REGRESSION
# Dataset: Breast Cancer Wisconsin
# ==============================================
print("\n--- STARTING EXPERIMENT 1.2: LOGISTIC REGRESSION ---")

# 1. Load Data
cancer = load_breast_cancer()
X_cls = pd.DataFrame(cancer.data, columns=cancer.feature_names)
y_cls = cancer.target

# 2. Preprocessing
X_train_cls, X_test_cls, y_train_cls, y_test_cls = train_test_split(X_cls, y_cls, test_size=0.2,
random_state=42)

# Scaling (Crucial for Logistic Regression convergence)
scaler_cls = StandardScaler()
X_train_cls_scaled = scaler_cls.fit_transform(X_train_cls)
X_test_cls_scaled = scaler_cls.transform(X_test_cls)

# 3. Model Training
log_reg = LogisticRegression(max_iter=1000)
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log_reg.fit(X_train_cls_scaled, y_train_cls)

# 4. Evaluation
y_pred_cls = log_reg.predict(X_test_cls_scaled)
print("Accuracy:", accuracy_score(y_test_cls, y_pred_cls))
print("\nClassification Report:\n", classification_report(y_test_cls, y_pred_cls))

# Visualizing Confusion Matrix
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test_cls, y_pred_cls), annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix: Logistic Regression')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()

# 5. Hyperparameter Tuning
print("\nPerforming Hyperparameter Tuning...")
param_grid_cls = {'C': [0.01, 0.1, 1, 10, 100], 'solver': ['liblinear', 'lbfgs']}
grid_cls = GridSearchCV(LogisticRegression(max_iter=2000), param_grid_cls, cv=5)
grid_cls.fit(X_train_cls_scaled, y_train_cls)

print(f"Best Hyperparameters: {grid_cls.best_params_}")
print(f"Best CV Accuracy: {grid_cls.best_score_:.4f}")
```

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1. Dataset Source

- **Experiment A (Linear):** California Housing Dataset. Originally from the StatLib repository.
- **Experiment B (Logistic):** Breast Cancer Wisconsin (Diagnostic) Dataset. Sourced from the UCI Machine Learning Repository.

2. Dataset Description

- **California Housing (Regression):**
  - **Size:** 20,640 samples.
  - **Features:** 8 numeric features (e.g., MedInc (median income), HouseAge, AveRooms, AveOccup).
  - **Target Variable:** MedHouseVal (Median house value in units of $100,000).
  - **Characteristics:** Continuous target variable; features vary significantly in scale.
- **Breast Cancer Wisconsin (Classification):**
  - **Size:** 569 samples.
  - **Features:** 30 numeric features computed from a digitized image of a fine needle aspirate (FNA) of a breast mass (e.g., radius, texture, perimeter, area).
  - **Target Variable:** Diagnosis (Malignant = 0, Benign = 1).

- **Characteristics:** Binary classification problem; highly correlated features.

3. Mathematical Formulation of the Algorithm

- **Linear Regression:**
  The goal is to find a linear relationship between input variables X and target y. The hypothesis function is:
  $$h_\theta(x) = \theta_0 + \theta_1x_1 + \theta_2x_2 + ... + \theta_nx_n$$
  The algorithm minimizes the **Mean Squared Error (MSE)** cost function:
  $$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2$$
- **Logistic Regression:**
  Used for binary classification. It applies the **Sigmoid function** to squash the linear output between 0 and 1:
  $$\sigma(z) = \frac{1}{1 + e^{-z}}$$
  The hypothesis represents the probability that $y=1$:
  $$h_\theta(x) = \sigma(\theta^T x)$$
  It minimizes the **Log-Loss (Cross-Entropy)** cost function.

4. Algorithm Limitations

- **Linear Regression:**
  - **Linearity Assumption:** Fails to capture complex, non-linear patterns in data.
  - **Outliers:** Extremely sensitive to outliers, which can skew the regression line significantly.
  - **Multicollinearity:** Performance degrades if independent variables are highly correlated.
- **Logistic Regression:**
  - **Linear Boundaries:** Can only solve problems where classes are linearly separable (unless feature engineering/kernels are used).
  - **Data Size:** Typically requires a large number of samples to achieve stable results.
  - **Overfitting:** Prone to overfitting if the number of features is greater than the number of observations (high dimensionality).

5. Methodology / Workflow

1. **Data Loading:** Imported datasets from the sklearn library.
2. **Preprocessing:**
   - Split data into Training (80%) and Testing (20%) sets.
   - **Standardization:** Applied StandardScaler to normalize feature scales (crucial for Logistic Regression and regularization).
3. **Model Training:**
   - Fitted LinearRegression for the housing data.
   - Fitted LogisticRegression for the cancer data.
4. **Evaluation:** Used test set to predict and calculated metrics (MSE/R2 for regression, Accuracy/Confusion Matrix for classification).
5. **Hyperparameter Tuning:** Used GridSearchCV to find optimal settings.

6. Performance Analysis

(Note: You will get exact numbers after running the code, but here is how to interpret them)

- **Linear Regression:**
    - **MSE (Mean Squared Error):** Lower is better. Indicates the average squared difference between estimated values and the actual value.
    - **R2 Score:** Closer to 1.0 is better. Indicates the proportion of variance in the dependent variable explained by the model.
- **Logistic Regression:**
    - **Accuracy:** Percentage of correct predictions.
    - **Confusion Matrix:** Shows True Positives, True Negatives, False Positives, and False Negatives. This helps identify if the model is biased toward one class (e.g., predicting "Benign" too often).

7. Hyperparameter Tuning

- **Linear Experiment (Ridge):**
    - **Parameter Tuned:** alpha (Regularization strength).
    - **Impact:** Higher alpha reduces overfitting by penalizing large coefficients. We tested [0.1, 1.0, 10.0, 100.0]. The code outputs the alpha that resulted in the best cross-validation R2 score.
- **Logistic Experiment:**
    - **Parameter Tuned:** C (Inverse of regularization strength).
    - **Impact:** Smaller C specifies stronger regularization. We also tuned the solver (algorithm for optimization). The code identifies the combination that yields the highest accuracy.

OUTPUT :

```
--- STARTING EXPERIMENT 1.1: LINEAR REGRESSION ---
Linear Regression MSE: 0.5559
Linear Regression R2 Score: 0.5758

Performing Hyperparameter Tuning (Ridge Regression)...
Best Alpha for Ridge: {'alpha': 0.1}
Best R2 Score (Ridge): 0.6115
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--- STARTING EXPERIMENT 1.2: LOGISTIC REGRESSION ---
Accuracy: 0.9736842105263158

Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.95      0.96        43
           1       0.97      0.99      0.98        71

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114
```

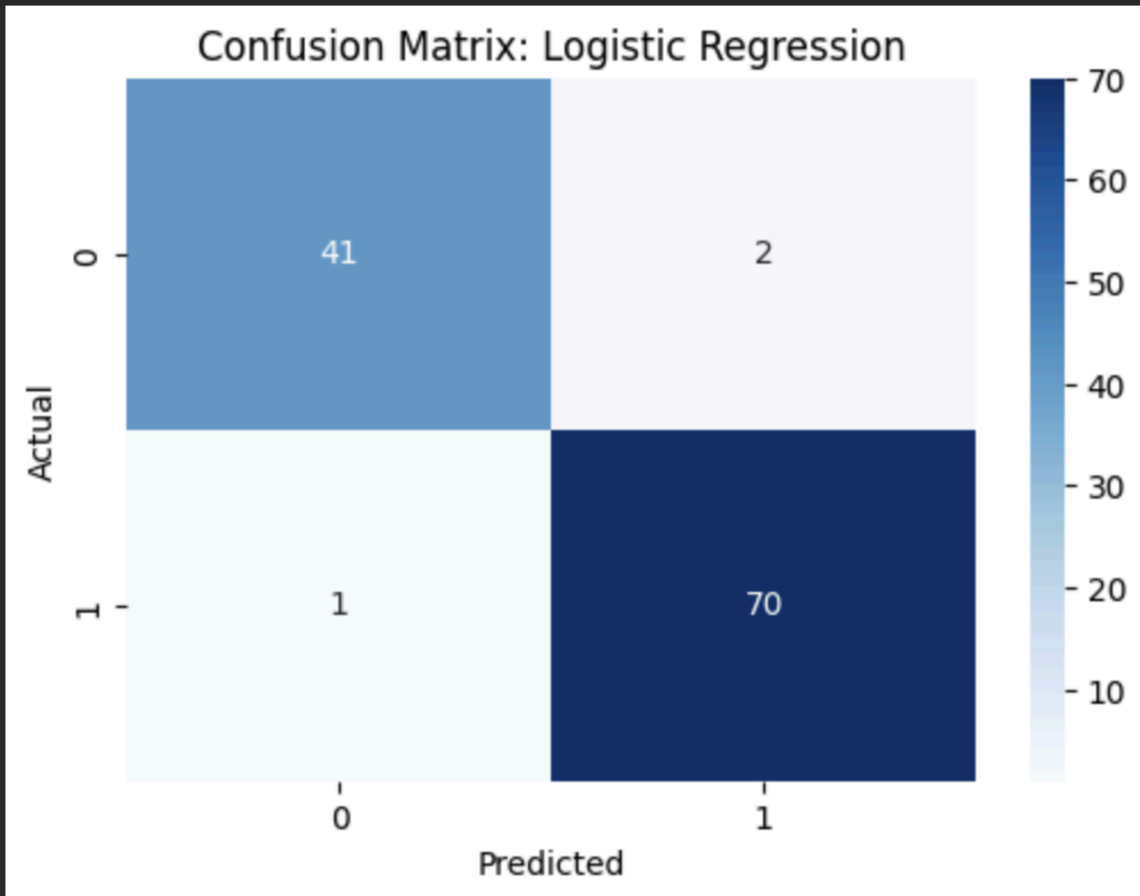


```
Performing Hyperparameter Tuning...
Best Hyperparameters: {'C': 0.1, 'solver': 'liblinear'}
Best CV Accuracy: 0.9780
```