Jupyter Classification with Logistic Regression\_Task4 Last Checkpoint: 18 hours ago Trusted File Edit View Run Kernel Settings Help JupyterLab ☐ # Python 3 (ipykernel) ○ **1** + % □ □ ▶ ■ C → Code **☆** □ ↑ ↓ 占 무 i # 1 Import required libraries import pandas as pd import numpy as np from sklearn.model\_selection import train\_test\_split from sklearn.preprocessing import StandardScaler from sklearn.linear\_model import LogisticRegression from sklearn.metrics import ( confusion\_matrix, classification\_report, roc\_auc\_score, roc\_curve, accuracy\_score, precision\_score, recall\_score import matplotlib.pyplot as plt import seaborn as sns # 🔼 Load dataset data = pd.read\_csv(r"D:\mydata\Elevate Labs\task4\data.csv", sep=',', encoding='utf-8') print("\nMissing Values:\n", data.isnull().sum()) print("\nData Info:") print(data.info()) print("\nDataset Shape:", data.shape) print("\nFirst 5 rows:\n", data.head()) # 🗾 Drop unwanted columns and handle missing values data = data.drop(['Unnamed: 32'], axis=1, errors='ignore') <class 'pandas.core.frame.DataFrame'> RangeIndex: 569 entries, 0 to 568 Data columns (total 33 columns): Non-Null Count Dtype Column id 569 non-null int64 diagnosis 569 non-null float64 radius\_mean 3 texture\_mean 569 non-null float64 float64 perimeter\_mean 569 non-null 569 non-null float64 5 area\_mean 6 smoothness\_mean 569 non-null float64 7 compactness\_mean 569 non-null float64 float64 8 concavity\_mean 569 non-null float64 9 concave points\_mean 569 non-null 10 symmetry\_mean 569 non-null float64 11 fractal\_dimension\_mean 569 non-null float64 12 radius\_se 569 non-null float64 [29]: # Define features and labels X = data.drop(['id', 'diagnosis'], axis=1, errors='ignore') y = data['diagnosis'].map({'M': 1, 'B': 0}) # Encode malignant as 1, benign as 0 print("\nX shape:", X.shape) print("y shape:", y.shape) print("\nValue Counts:\n", y.value\_counts()) # Verify no missing values print("\nAny NaN in X?", X.isna().sum().sum() > 0) print("Any NaN in y?", y.isna().sum() > 0) # 🖪 Split the data safely X\_train, X\_test, y\_train, y\_test = train\_test\_split( X, y, test\_size=0.3, random\_state=42, stratify=y # stratify preserves class balance print("\nTrain size:", X\_train.shape, "Test size:", X\_test.shape) X shape: (569, 30) y shape: (569,) Value Counts: diagnosis 357 212 Name: count, dtype: int64 Any NaN in X? False Any NaN in y? False Train size: (398, 30) Test size: (171, 30) # 5 Feature scaling scaler = StandardScaler() X\_train\_scaled = scaler.fit\_transform(X\_train) X\_test\_scaled = scaler.transform(X\_test) # 👩 Train the Logistic Regression model model = LogisticRegression(random\_state=42, max\_iter=1000) model.fit(X\_train\_scaled, y\_train) # 1 Model predictions y\_pred = model.predict(X\_test\_scaled) y\_pred\_prob = model.predict\_proba(X\_test\_scaled)[:, 1] # 🛭 Confusion Matrix cm = confusion\_matrix(y\_test, y\_pred) sns.heatmap(cm, annot=True, fmt='d', cmap='Blues') plt.title("Confusion Matrix") plt.xlabel("Predicted") plt.ylabel("Actual") plt.show() # 9 Classification Report print("\nClassification Report:\n", classification\_report(y\_test, y\_pred)) Confusion Matrix - 100 106 1 80 0 -- 60 Actual - 40 60 - 20 0 1 Predicted Classification Report: precision recall f1-score support 0 107 0.96 0.99 0.98 1 64 0.98 0.94 0.96 171 accuracy 0.97 171 macro avg 0.97 0.96 0.97 weighted avg 171 0.97 0.97 0.97 [31]: # 1 / ROC-AUC Curve fpr, tpr, thresholds = roc\_curve(y\_test, y\_pred\_prob) roc\_auc = roc\_auc\_score(y\_test, y\_pred\_prob) plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc\_auc:.2f})') plt.plot([0, 1], [0, 1], 'k--') plt.xlabel("False Positive Rate") plt.ylabel("True Positive Rate") plt.title("ROC-AUC Curve") plt.legend() plt.show() # 1 Threshold tuning example threshold = 0.6 y\_pred\_custom = (y\_pred\_prob >= threshold).astype(int) print(f"\nPerformance at threshold {threshold}:") print(f"Accuracy: {accuracy\_score(y\_test, y\_pred\_custom):.3f}") print(f"Precision: {precision\_score(y\_test, y\_pred\_custom):.3f}") print(f"Recall: {recall score(y test, y pred custom):.3f}") **ROC-AUC Curve** 1.0 0.8 True Positive Rate 0.6 0.4 0.2 ROC curve (AUC = 1.00) 0.0 0.2 0.8 0.4 0.0 0.6 1.0 False Positive Rate Performance at threshold 0.6: Accuracy: 0.971 Precision: 1.000 Recall: 0.922