Logistic Regression Lab for Data Breach Dataset

Introduction to Machine Learning - Homework Assignment

Overview

In this lab, you'll learn about logistic regression, a fundamental machine learning algorithm used for classification problems. You'll work with a real-world data breach dataset to build a model that predicts whether a security breach will affect a large number of individuals.

Learning Objectives:

- Understand what logistic regression is and when to use it
- Learn how to prepare data for machine learning
- Build and evaluate a simple logistic regression model
- Interpret the results of your model

Part 1: Introduction to Logistic Regression

What is Logistic Regression?

Logistic regression is a statistical method used for predicting binary outcomes (Yes/No, True/False, 0/1). Unlike linear regression which predicts continuous values, logistic regression predicts the probability that an instance belongs to a particular class.

Examples of logistic regression applications:

- Predicting whether an email is spam or not
- Determining if a patient has a disease based on symptoms
- Forecasting if a customer will make a purchase

About the Dataset

The dataset you'll be working with contains information about data breaches reported to various state Attorneys General offices. Each row represents a separate breach incident with details about:

- The organization affected
- The type of breach
- When it happened
- How many individuals were affected
- What type of information was compromised

Part 2: Data Exploration

Loading the Data

We'll start by loading the data and examining its structure.

Import Python libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression


# Load the dataset
# The read_excel function loads data from Excel files
df = pd.read_csv('https://github.com/scottalanturner/AI-ML-Labs/blob/main/Logistic-Regression/data/Data_Breach_Chronology_sample.csv?raw=true

# Display the first few rows
print("First 5 rows of the dataset:")
df.head()
```

```
First 5 rows of the dataset:
```

	id	source	org_name	acceptable_names	org_name_explanation	reported_date	breach_date	end_breach_date	incident_det
0	280b456e-2397-5db7-8954-44d2d2cda55a	IN	AboundWealth-DataBreach	NaN	The Indiana Office of the Attorney General rep...	2019-01-28	2018-12-23	UNKN	The Indiana (of the Att General
1	8a3c84d1-f48e-53a4-8396-db1024f87115	ME	Five Guys Holdings, Inc.	Five Guys	The Maine Office of the Attorney General repor...	2018-11-30	2018-05-23	UNKN	The Maine Offi the Att General re
2	69c88f84-52aa-5e1e-aa95-7fce1c7e0e49	ME	Phillip Galyen P.C.	Galyen, Galyen Law Firm	The breach was reported by the Maine Office of...	2021-05-14	2021-03	UNKN	The Maine Offi the Att General re
3	c9ebf0b9-7234-57c4-91f5-49417e433094	ME	Old City Coffee, Inc.	Old City Coffee, Old City	The Maine Office of the Attorney General repor...	2021-06-21	2021-02	2021-03-02	The Maine Offi the Att General re
4	da2336b1-92b5-56dc-a7f2-3d33d750c38c	VT	Cadence Bank	Cadence	The data breach notification letter clearly id...	2023-11-22	2023-05-28	2023-05-31	The Vermont (of the Att General

5 rows × 37 columns

Understanding the Dataset

Let's look at some basic information about our dataset.

```
# Check the size of our dataset
print(f"Dataset dimensions: {df.shape[0]} rows and {df.shape[1]} columns")

# Get column names
print("\nColumn names:")
for col in df.columns:
    print(f"- {col}")

# Check for missing values
print("\nMissing values in each column:")
print(df.isnull().sum())

# Get summary statistics
print("\nSummary statistics for numeric columns:")
df.describe()
```

```
Dataset dimensions: 1000 rows and 37 columns

Column names:
- id
- source
- org_name
- acceptable_names
- org_name_explanation
- reported_date
- breach_date
- end_breach_date
- incident_details
- date_info_explanation
- information_affected
- information_affected_explanation
- organization_type
- organization_type_explanation
- breach_type
- breach_type_explanation
- group_uuid
- normalized_org_name
- normalized_org_name_explanation
- group_org_breach_type
- group_org_breach_type_explanation
- group_org_type
- group_org_type_explanation
- total_affected
- residents_affected
- impact_info_explanation
- breach_location_street
- breach_location_city
- breach_location_state
- breach_location_zip
- breach_location_country
- breach_location_explanation
- tags
- source_url
- notification_url_original
- created_at
- updated_at

Missing values in each column:
id                                    0
source                                0
org_name                              0
acceptable_names                    576
org_name_explanation                  0
reported_date                         0
breach_date                           0
end_breach_date                       0
incident_details                      0
date_info_explanation                 0
information_affected                  0
information_affected_explanation      0
organization_type                     0
organization_type_explanation         0
breach_type                           0
breach_type_explanation               0
group_uuid                            0
normalized_org_name                   0
normalized_org_name_explanation       0
group_org_breach_type                 0
group_org_breach_type_explanation     0
group_org_type                        0
group_org_type_explanation            0
total_affected                        0
residents_affected                    0
impact_info_explanation               0
breach_location_street                0
breach_location_city                  0
breach_location_state                 0
breach_location_zip                   0
breach_location_country               0
breach_location_explanation           0
tags                                115
source_url                           24
notification_url_original            37
created_at                            0
updated_at                            0
dtype: int64

Summary statistics for numeric columns:
```

	id	source	org_name	acceptable_names	org_name_explanation	reported_date	breach_date	end_breach_date	inciden

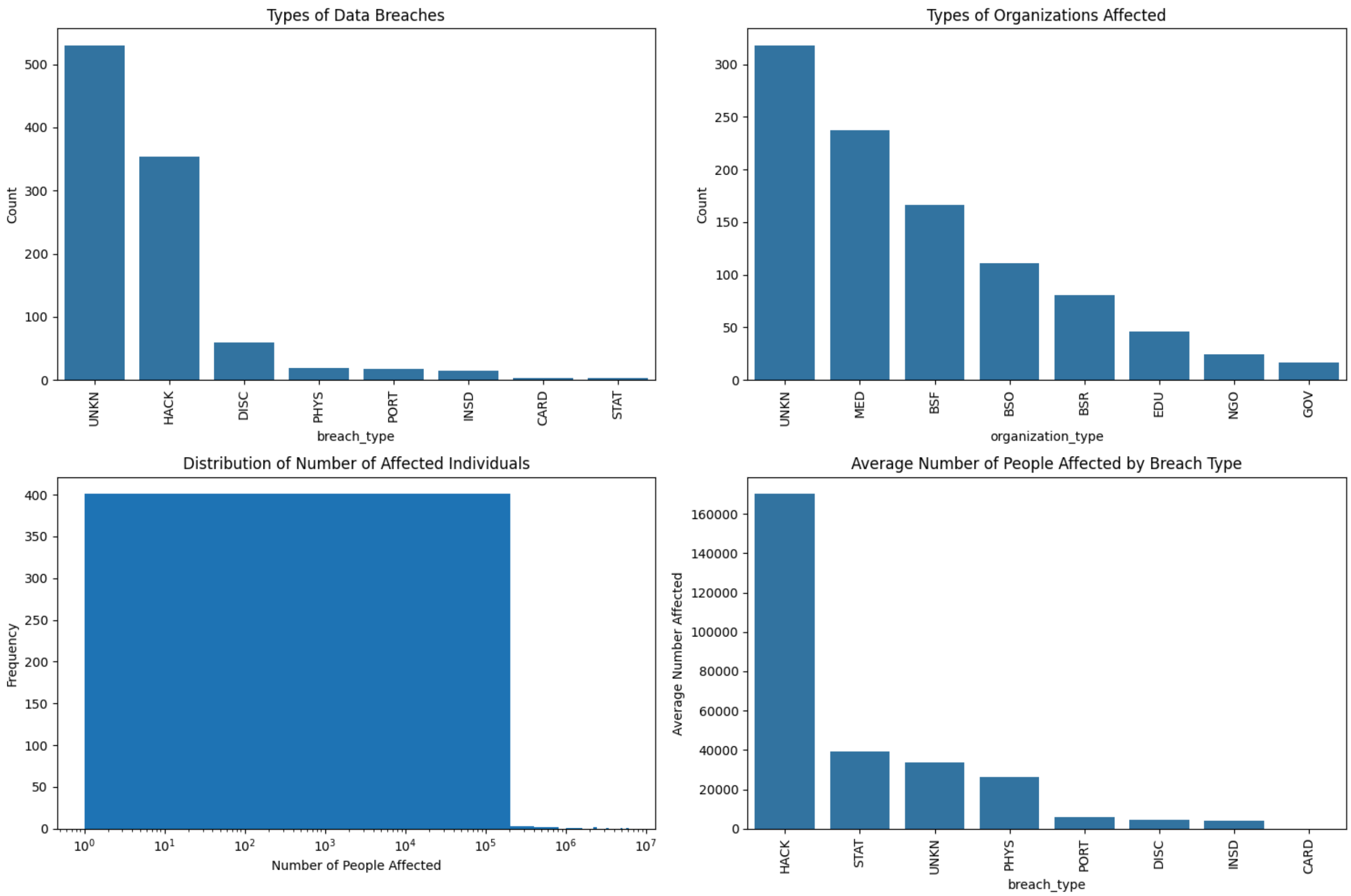
count	1000	1000	1000	424	1000	1000	1000	1000	
unique	1000	15	905	417	1000	847	486	238	
top	fe8f8d9e-5114-5be6-839e-83f61b1385fc	MA	The Village Bank	Cencora, Lash Group	The Massachusetts Office of Consumer Affairs a...	2016-04-11	UNKN	UNKN	On July 2 Mass O
freq	1	311	9	2	1	4	434	727	

4 rows × 37 columns

Data Visualization

Let's create some visualizations to better understand our data.

```
# Create a figure with multiple subplots
plt.figure(figsize=(15, 10))

# Plot 1: Distribution of breach types
plt.subplot(2, 2, 1)
breach_counts = df['breach_type'].value_counts()
sns.barplot(x=breach_counts.index, y=breach_counts.values)
plt.title('Types of Data Breaches')
plt.xticks(rotation=90)
plt.ylabel('Count')

# Plot 2: Distribution of organization types
plt.subplot(2, 2, 2)
org_counts = df['organization_type'].value_counts()
sns.barplot(x=org_counts.index, y=org_counts.values)
plt.title('Types of Organizations Affected')
plt.xticks(rotation=90)
plt.ylabel('Count')

# Plot 3: Number of affected individuals (log scale)
plt.subplot(2, 2, 3)
# Convert to numeric and handle non-numeric values
df['total_affected_numeric'] = pd.to_numeric(df['total_affected'], errors='coerce')
# Filter out missing values for the plot
df_filtered = df[df['total_affected_numeric'].notna()]
plt.hist(df_filtered['total_affected_numeric'], bins=30)
plt.title('Distribution of Number of Affected Individuals')
plt.xlabel('Number of People Affected')
plt.ylabel('Frequency')
plt.xscale('log')  # Use log scale for better visualization

# Plot 4: Breach type vs average number affected
plt.subplot(2, 2, 4)
breach_impact = df.groupby('breach_type')['total_affected_numeric'].mean().sort_values(ascending=False)
sns.barplot(x=breach_impact.index, y=breach_impact.values)
plt.title('Average Number of People Affected by Breach Type')
plt.xticks(rotation=90)
plt.ylabel('Average Number Affected')

plt.tight_layout()
plt.savefig('data_exploration.png')  # Save for your report
plt.show()
```



Questions to consider:

1. Which types of breaches are most common?
2. What types of organizations suffer the most breaches?
3. Is there a relationship between breach type and number of people affected?

Part 3: Data Preparation

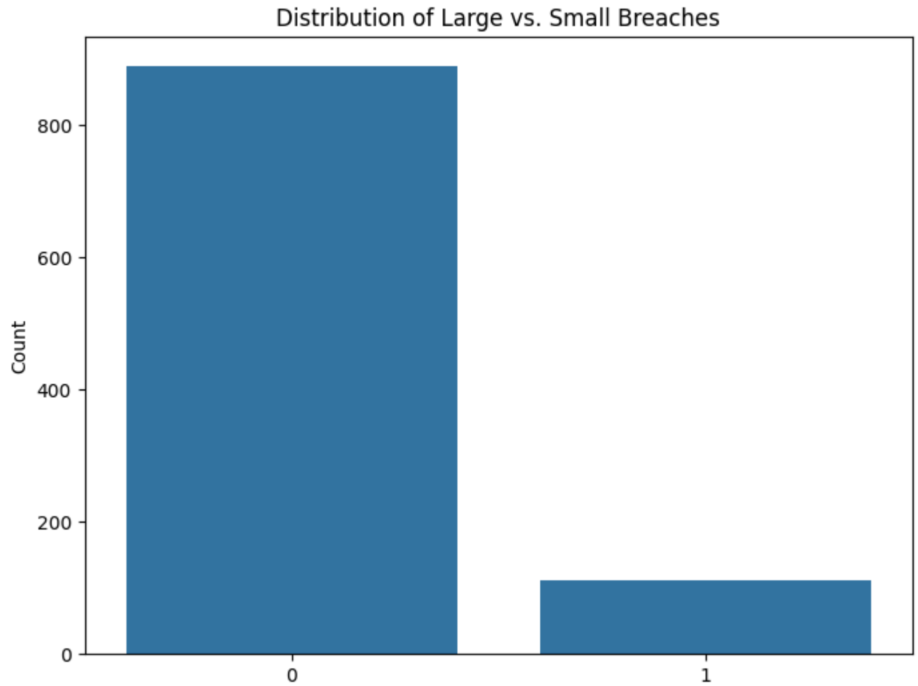
Creating a Target Variable

We'll define a binary target variable for our logistic regression model: whether a breach affects a "large" number of individuals or not.

```
# Define what makes a "large" breach (more than 10,000 individuals affected)
threshold = 10000

# Create our target variable
df['large_breach'] = (df['total_affected_numeric'] > threshold).astype(int)

# Display the distribution of our target variable
print(f"Number of large breaches: {df['large_breach'].sum()}")
print(f"Number of small breaches: {len(df) - df['large_breach'].sum()}")
print(f"Percentage of large breaches: {df['large_breach'].mean() * 100:.2f}%")

# Visualize the distribution
plt.figure(figsize=(8, 6))
sns.countplot(x='large_breach', data=df)
plt.title('Distribution of Large vs. Small Breaches')
plt.xlabel('Large Breach (1 = Yes, 0 = No)')
```

```
plt.ylabel('Count')
plt.savefig('target_distribution.png')  # Save for your report
plt.show()
```

```
Number of large breaches: 111
Number of small breaches: 889
Percentage of large breaches: 11.10%
```



Preparing Features

Now we need to prepare our feature variables (predictors) for the model.

```
# Select features we want to use for prediction
# We'll choose the breach type and organization type
selected_features = ['breach_type', 'organization_type']

# Handle non-numeric values in breach_type and organization_type
# We'll convert categorical variables to numeric using one-hot encoding
from sklearn.preprocessing import OneHotEncoder

# Select only rows with valid target values
df_model = df.dropna(subset=['large_breach'])

# Create encoder object
encoder = OneHotEncoder(sparse_output=False, drop='first')  # drop first category to avoid multicollinearity

# Apply one-hot encoding to our categorical variables
encoded_features = encoder.fit_transform(df_model[selected_features])

# Get the feature names after encoding
feature_names = encoder.get_feature_names_out(selected_features)
print("Feature names after encoding:")
print(feature_names)

# Create a DataFrame with the encoded features
X = pd.DataFrame(encoded_features, columns=feature_names)

# Define the target variable
y = df_model['large_breach']

# Show the first few rows of prepared data
X.head()
```

```
Feature names after encoding:
['breach_type_DISC' 'breach_type_HACK' 'breach_type_INSD'
 'breach_type_PHYS' 'breach_type_PORT' 'breach_type_STAT'
 'breach_type_UNKN' 'organization_type_BSO' 'organization_type_BSR'
 'organization_type_EDU' 'organization_type_GOV' 'organization_type_MED'
 'organization_type_NGO' 'organization_type_UNKN']
```

	breach_type_DISC	breach_type_HACK	breach_type_INSD	breach_type_PHYS	breach_type_PORT	breach_type_STAT	breach_type_UNKN	organiz
0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
2	0.0	1.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	1.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	1.0	0.0	0.0	0.0	0.0	0.0	

Next steps: Generate code with X | View recommended plots | New interactive sheet

Double-click (or enter) to edit

Part 4: Building the Model

Splitting the Data

We'll split our data into training and testing sets.

```
# Import necessary function
from sklearn.model_selection import train_test_split

# Split the data into training (80%) and testing (20%) sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Check the shape of our training and testing sets
print(f"Training set shape: {X_train.shape}")
print(f"Testing set shape: {X_test.shape}")
```

```
Training set shape: (800, 14)
Testing set shape: (200, 14)
```

Creating and Training the Model

```
# Import the logistic regression model
from sklearn.linear_model import LogisticRegression

# Create a logistic regression model
model = LogisticRegression(random_state=42)

# Train the model using the training data
model.fit(X_train, y_train)

# Display the model coefficients
print("Model coefficients:")
for feature, coefficient in zip(X.columns, model.coef_[0]):
    print(f"{feature}: {coefficient:.4f}")

# Display the intercept
print(f"Intercept: {model.intercept_[0]:.4f}")
```

```
Model coefficients:
breach_type_DISC: -0.4668
breach_type_HACK: 0.5745
breach_type_INSD: 0.1473
breach_type_PHYS: -0.3099
breach_type_PORT: -0.3620
breach_type_STAT: 0.4750
breach_type_UNKN: 0.0093
organization_type_BSO: 0.5194
organization_type_BSR: -0.2664
organization_type_EDU: -0.0977
organization_type_GOV: 0.5536
```

```
organization_type_MED: 1.5288
organization_type_NGO: -0.0918
organization_type_UNKN: 0.4536
Intercept: -3.0345
```

Understanding Model Coefficients:

- **Positive coefficients**: Indicate features that increase the probability of a large breach
- **Negative coefficients**: Indicate features that decrease the probability of a large breach
- **Larger magnitude**: Indicates a stronger effect

Part 5: Evaluating the Model

Making Predictions

```
# Use the model to make predictions on the test set
y_pred = model.predict(X_test)

# Compare the first few actual values vs. predictions
comparison = pd.DataFrame({'Actual': y_test.values, 'Predicted': y_pred})
print("First 10 actual vs predicted values:")
print(comparison.head(10))
```

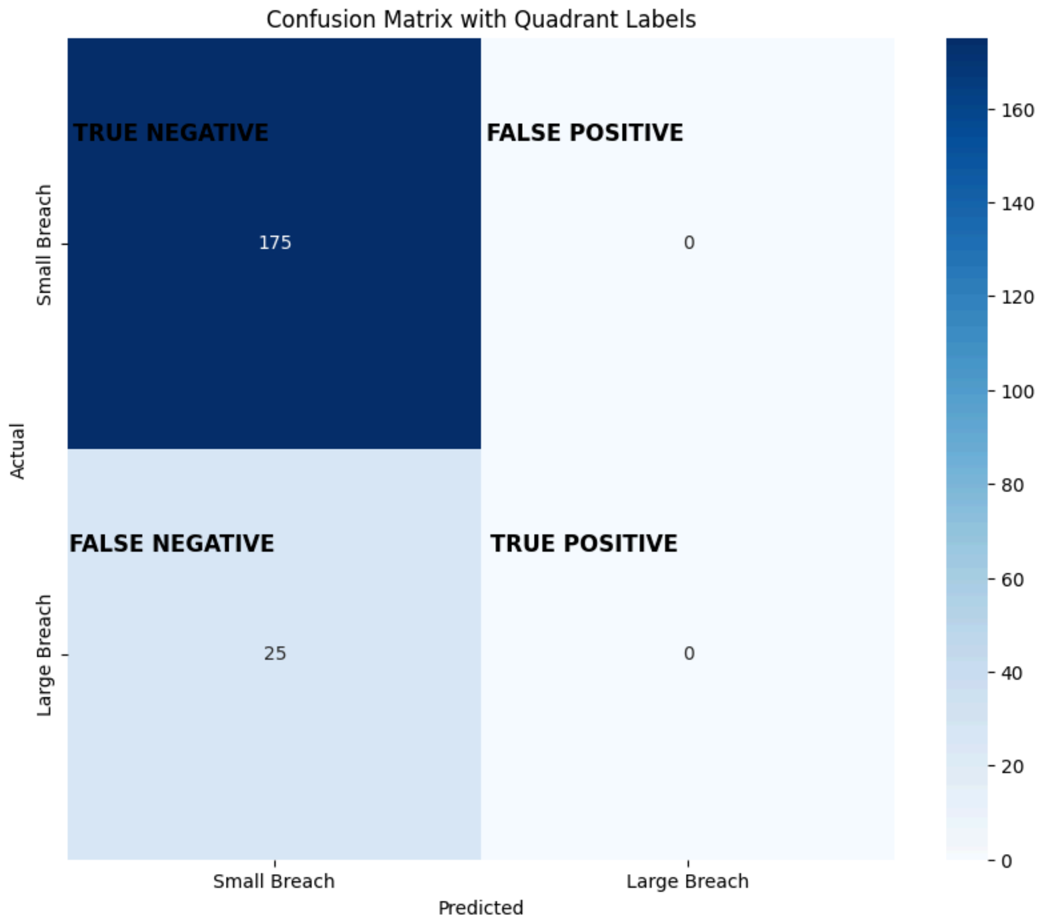
```
First 10 actual vs predicted values:
   Actual  Predicted
0       0          0
1       0          0
2       0          0
3       0          0
4       0          0
5       0          0
6       0          0
7       0          0
8       0          0
9       1          0
```

Model Accuracy

```
# Import necessary metrics
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Model accuracy: {accuracy:.4f} ({accuracy*100:.2f}%)")

# Display confusion matrix with labeled quadrants
conf_matrix = confusion_matrix(y_test, y_pred)

# Create a figure
plt.figure(figsize=(10, 8))

# Create the heatmap
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Small Breach', 'Large Breach'],
            yticklabels=['Small Breach', 'Large Breach'])

# Add quadrant labels with arrows
plt.text(0.25, 0.25, "TRUE NEGATIVE", horizontalalignment='center',
         size=12, color='black', weight='bold')
plt.text(1.25, 0.25, "FALSE POSITIVE", horizontalalignment='center',
         size=12, color='black', weight='bold')
plt.text(0.25, 1.25, "FALSE NEGATIVE", horizontalalignment='center',
         size=12, color='black', weight='bold')
plt.text(1.25, 1.25, "TRUE POSITIVE", horizontalalignment='center',
         size=12, color='black', weight='bold')

# Labels and title
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix with Quadrant Labels')
plt.savefig('confusion_matrix.png')  # Save for your report
plt.show()
```

```
# Add explanation for students
print("\nUnderstanding the Confusion Matrix:")
print("- TRUE NEGATIVE (TN): Correctly predicted Small Breach")
print("- FALSE POSITIVE (FP): Incorrectly predicted Large Breach when actually Small")
print("- FALSE NEGATIVE (FN): Incorrectly predicted Small Breach when actually Large")
print("- TRUE POSITIVE (TP): Correctly predicted Large Breach")
print(f"\nAccuracy: {(conf_matrix[0,0] + conf_matrix[1,1])/conf_matrix.sum():.4f}")
print(f"Error Rate: {(conf_matrix[0,1] + conf_matrix[1,0])/conf_matrix.sum():.4f}")
```

```
Model accuracy: 0.8750 (87.50%)
```




```
Understanding the Confusion Matrix:
- TRUE NEGATIVE (TN): Correctly predicted Small Breach
- FALSE POSITIVE (FP): Incorrectly predicted Large Breach when actually Small
- FALSE NEGATIVE (FN): Incorrectly predicted Small Breach when actually Large
- TRUE POSITIVE (TP): Correctly predicted Large Breach
```

Understanding the Confusion Matrix:

- **True Positives (TP)**: Correctly predicted large breaches
- **True Negatives (TN)**: Correctly predicted small breaches
- **False Positives (FP)**: Small breaches incorrectly predicted as large
- **False Negatives (FN)**: Large breaches incorrectly predicted as small

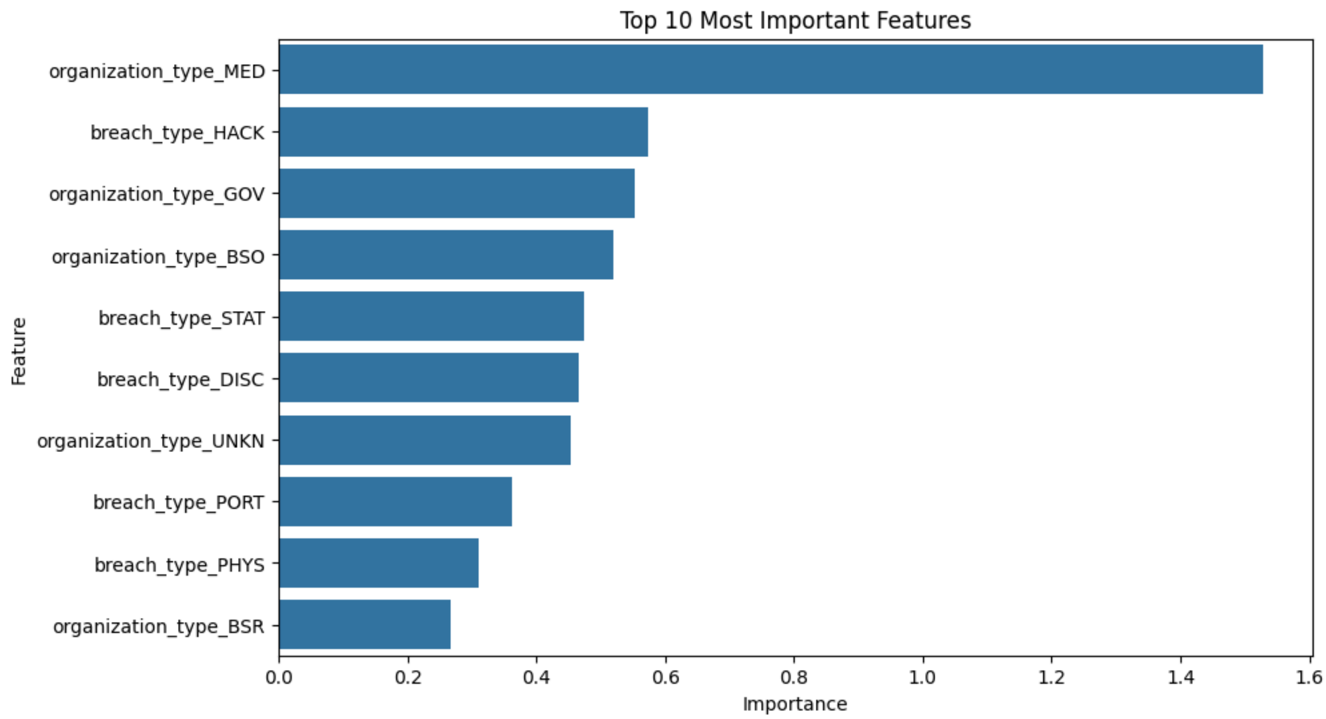
Understanding Classification Metrics:

- **Precision**: Percentage of predicted large breaches that are actually large
- **Recall**: Percentage of actual large breaches that were correctly identified
- **F1-score**: Harmonic mean of precision and recall

Part 6: Conclusion and Reflection

Model Interpretation

```
# Let's see which features are most important
feature_importance = pd.DataFrame({
    'Feature': X.columns,
    'Importance': np.abs(model.coef_[0])
})
feature_importance = feature_importance.sort_values('Importance', ascending=False)

plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance.head(10))
plt.title('Top 10 Most Important Features')
plt.savefig('feature_importance.png')  # Save for your report
plt.show()
```



Reflection Questions

Take some time to reflect on the following questions:

1. What does our logistic regression model predict in this context?
2. Which features have the strongest influence on whether a breach will be large?
3. What are the limitations of our model?
4. How could we improve the model's performance?