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=tru

# 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 Off 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 Off 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 Off 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	incident_det

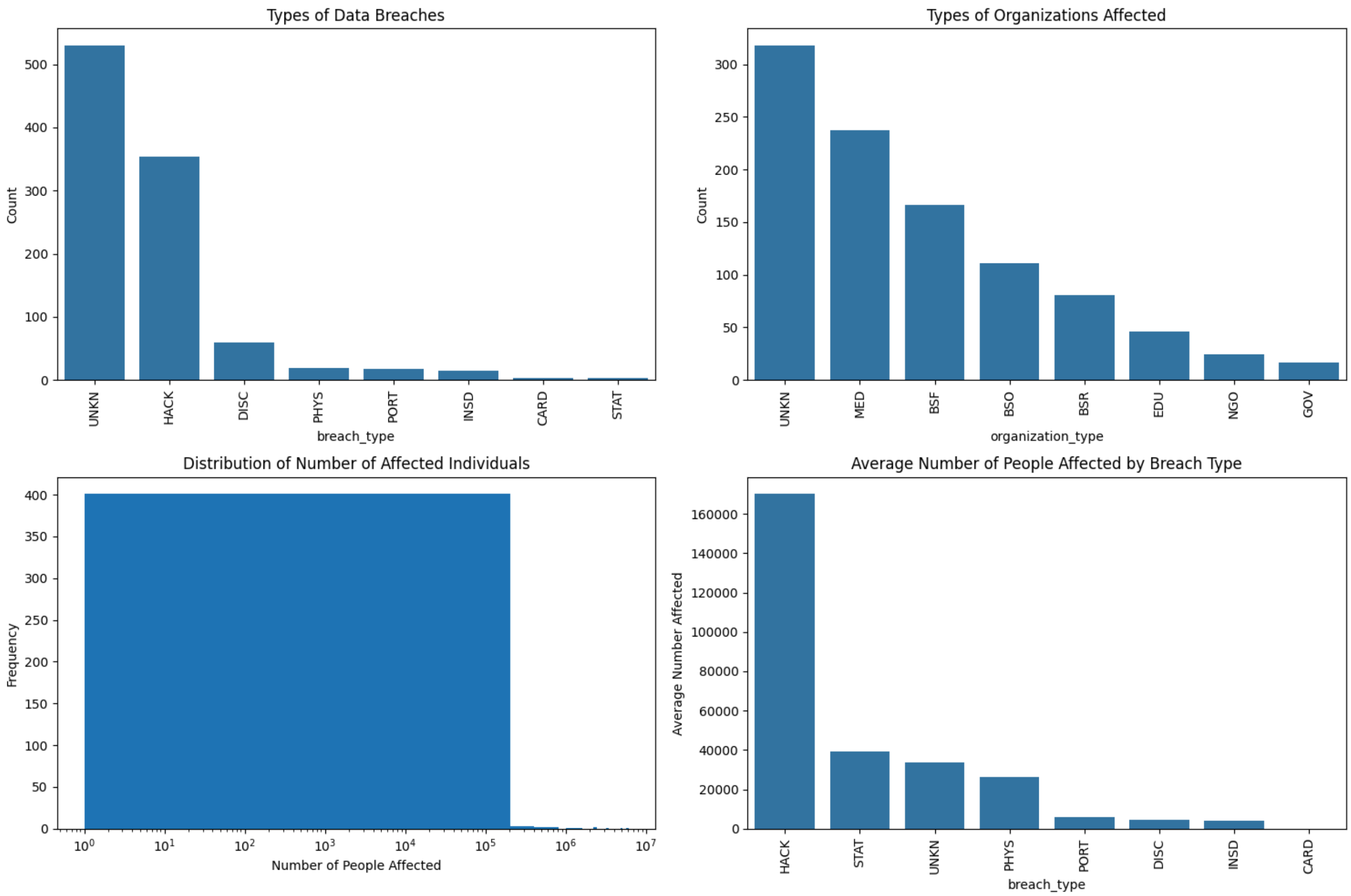
count	1000	1000	1000	424	1000	1000	1000	1000	
unique	1000	15	905	417	1000	847	486	238	
top	fe8f8d9e-5114-5be6-839e-83f61b1385fc	MA	The Village Bank	Cencora, Lash Group	The Massachusetts Office of Consumer Affairs a...	2016-04-11	UNKN	UNKN	On July 2, 2 the Massachu Office o
freq	1	311	9	2	1	4	434	727	

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

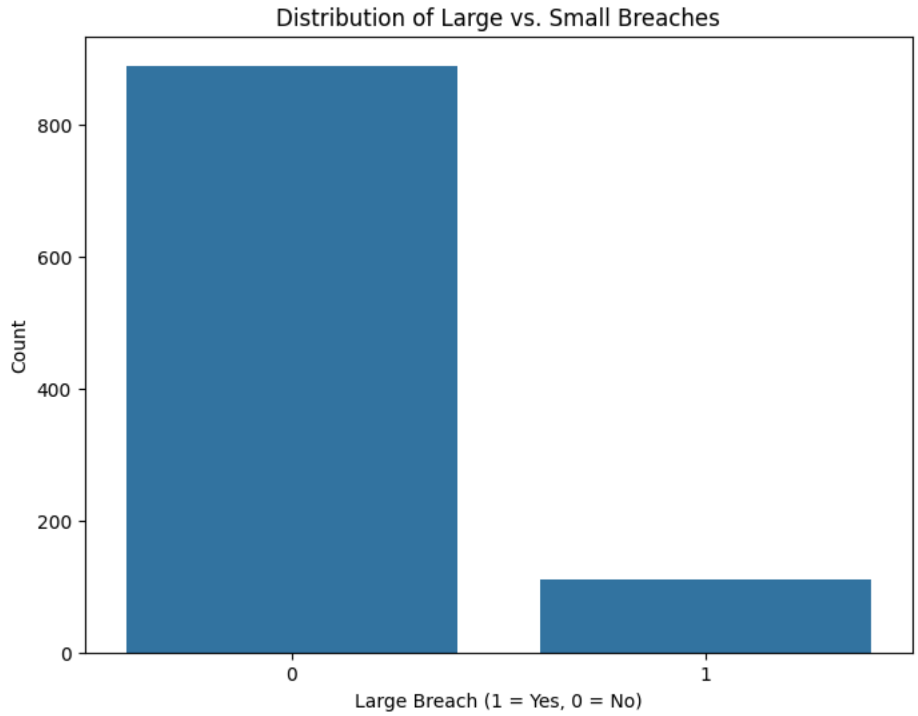
Creating a Target Variable

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))
```

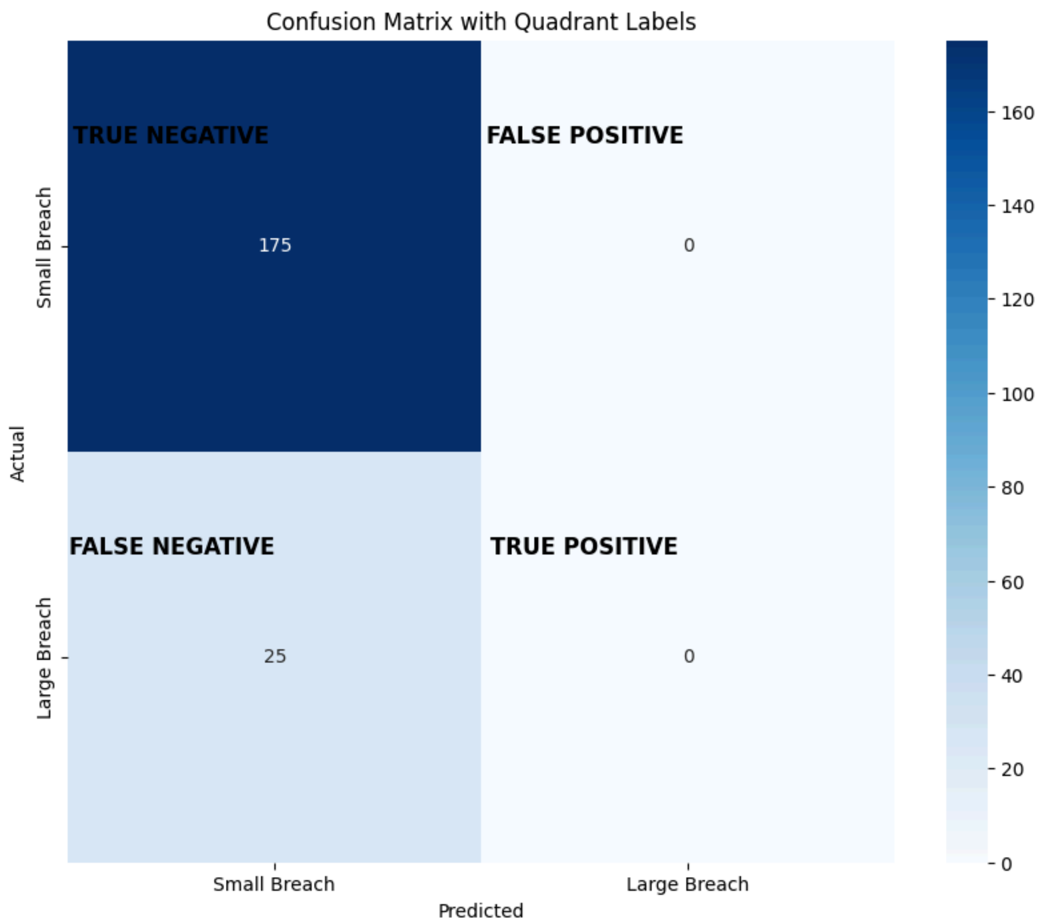
```
First 10 actual vs predicted values:
   Actual  Predicted
0       0          0
1       0          0
2       0          0
3       0          0
4       0          0
5       0          0
6       0          0
7       0          0
8       0          0
9       1          0
```

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

Accuracy: 0.8750
Error Rate: 0.1250
```

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

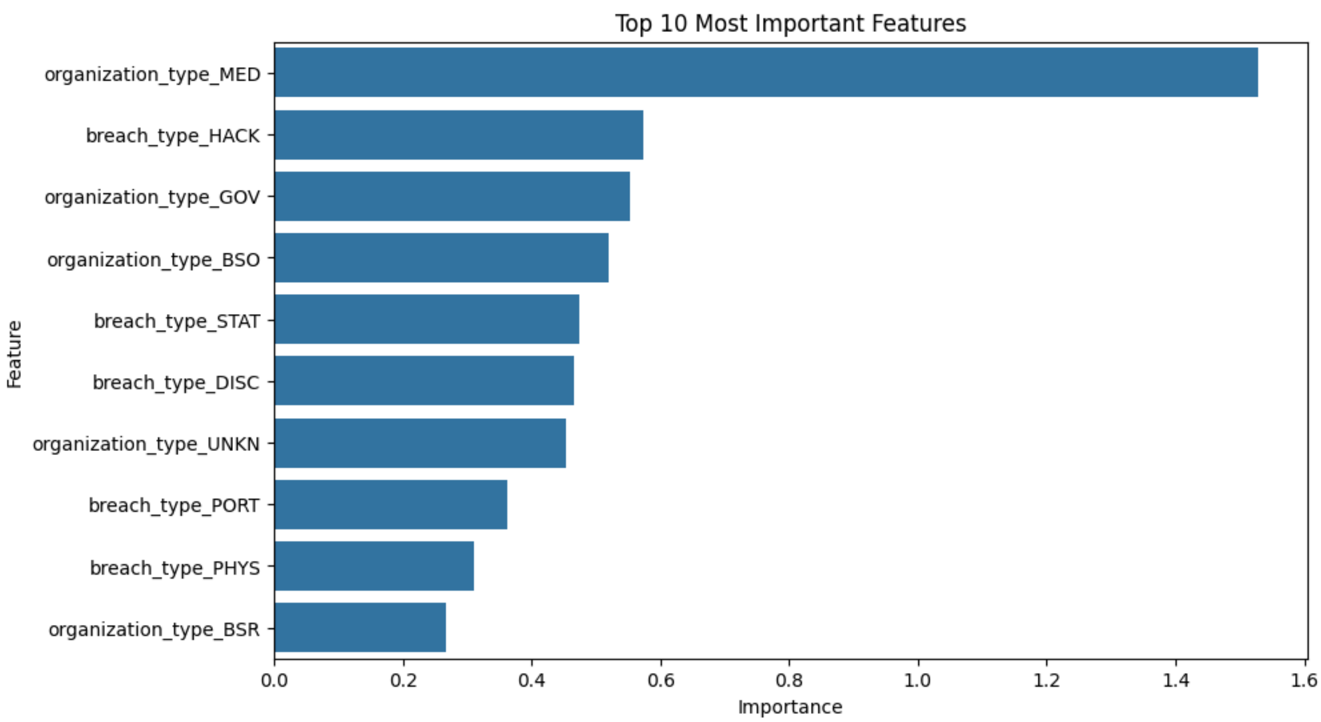
Understanding Classification Metrics:

- **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?
5. What other questions could we answer with this dataset?

Homework Deliverables

Please submit the following:

1. **This completed Jupyter Notebook in your Git repo**
    - Run all cells and export the notebook as PDF
    - Include all outputs, especially visualizations
    - Add the notebook to your repo
2. **Written responses (3-5 sentences each):**

- Type your responses in this notebook, by adding a markdown cell below. Answer each question:
- What does logistic regression predict in this context?
- Which features seem most important in predicting large breaches?
- What are the limitations of this model? HINT: There is a problem with the accuracy of this model