

```
!pip install pycountry-convert

Collecting pycountry-convert
  Downloading pycountry_convert-0.7.2-py3-none-any.whl.metadata (7.2 kB)
Collecting pprintpp>=0.3.0 (from pycountry-convert)
  Downloading pprintpp-0.4.0-py2.py3-none-any.whl.metadata (7.9 kB)
Collecting pycountry>=16.11.27.1 (from pycountry-convert)
  Downloading pycountry-24.6.1-py3-none-any.whl.metadata (12 kB)
Requirement already satisfied: pytest>=3.4.0 in /usr/local/lib/python3.12/dist-packages (from pycountry-convert) (8.4.2)
Collecting pytest-mock>=1.6.3 (from pycountry-convert)
  Downloading pytest_mock-3.15.1-py3-none-any.whl.metadata (3.9 kB)
Collecting pytest-cov>=2.5.1 (from pycountry-convert)
  Downloading pytest_cov-7.0.0-py3-none-any.whl.metadata (31 kB)
Collecting repoze.lru>=0.7 (from pycountry-convert)
  Downloading repoze.lru-0.7-py3-none-any.whl.metadata (1.1 kB)
Requirement already satisfied: wheel>=0.30.0 in /usr/local/lib/python3.12/dist-packages (from pycountry-convert) (0.45.1)
Requirement already satisfied: inicfg>=1 in /usr/local/lib/python3.12/dist-packages (from pytest>=3.4.0->pycountry-convert) (Requirement already satisfied: packaging>=20 in /usr/local/lib/python3.12/dist-packages (from pytest>=3.4.0->pycountry-convert))
Requirement already satisfied: pluggy<2,>=1.5 in /usr/local/lib/python3.12/dist-packages (from pytest>=3.4.0->pycountry-convert)
Requirement already satisfied: pygments>=2.7.2 in /usr/local/lib/python3.12/dist-packages (from pytest>=3.4.0->pycountry-convert)
Collecting coverage>=7.10.6 (from coverage[toml]>=7.10.6->pytest-cov>=2.5.1->pycountry-convert)
  Downloading coverage-7.12.0-cp312-cp312-manylinux1_x86_64.manylinux_2_28_x86_64.manylinux_2_5_x86_64.whl.metadata (9.1 kB)
Downloading pycountry_convert-0.7.2-py3-none-any.whl (13 kB)
Downloading pprintpp-0.4.0-py2.py3-none-any.whl (16 kB)
Downloading pycountry-24.6.1-py3-none-any.whl (6.3 MB)
  _____ 6.3/6.3 MB 51.4 MB/s eta 0:00:00
Downloading pytest_cov-7.0.0-py3-none-any.whl (22 kB)
Downloading pytest_mock-3.15.1-py3-none-any.whl (10 kB)
Downloading repoze.lru-0.7-py3-none-any.whl (10 kB)
Downloading coverage-7.12.0-cp312-cp312-manylinux1_x86_64.manylinux_2_28_x86_64.manylinux_2_5_x86_64.whl (252 kB)
  _____ 252.3/252.3 kB 13.4 MB/s eta 0:00:00
Installing collected packages: repoze.lru, pprintpp, pycountry, coverage, pytest-mock, pytest-cov, pycountry-convert
Successfully installed coverage-7.12.0 pprintpp-0.4.0 pycountry-24.6.1 pycountry-convert-0.7.2 pytest-cov-7.0.0 pytest-mock-3.15
```

Import needed libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
sns.set_style('whitegrid')

from sklearn.model_selection import cross_validate
from warnings import simplefilter
import warnings
warnings.filterwarnings("ignore")

import pycountry_convert as pc
```

Upload file

```
from google.colab import files
uploaded = files.upload()

Choose Files randomdata.csv
randomdata.csv(text/csv) - 27659221 bytes, last modified: 3/14/2022 - 100% done
Saving randomdata.csv to randomdata.csv
```

```
data = pd.read_csv('randomdata.csv')
```

```
data.head()
```

	Unnamed: 0	Customer Name	Customer_Address	Company Name	Claim Reason	Data confidentiality	Claim Amount	Category Premium	Premium/Amount Ratio	Claim Request output	BMI	Churn
0	0	Christine Payne	7627 Anderson Rest Apt. 265,Lake Heather, DC 3...	Williams, Henderson and Perez	Travel	Low	377	4794	0.078640	No	21	
1	1	Tony Fernandez	3953 Cindy Brook Apt. 147,East Lindatown, TN 4...	Moore- Goodwin	Medical	High	1440	14390	0.100069	No	24	
2	2	Christopher Kim	8693 Walters Mountains,South Tony, TX 88407	Smith- Holmes	Phone	Medium	256	1875	0.136533	No	18	
3	3	Nicole Allen	56926 Webster Coves,Shawnmouth, NV 04853	Harrell- Perez	Phone	Medium	233	1875	0.124267	No	24	

```
df = data.copy().drop(["Unnamed: 0", "Customer Name", "Customer_Address", "Company Name"], axis = 1)
df.head()
```

	Claim Reason	Data confidentiality	Claim Amount	Category Premium	Premium/Amount Ratio	Claim Request output	BMI	Churn
0	Travel	Low	377	4794	0.078640	No	21	Yes
1	Medical	High	1440	14390	0.100069	No	24	Yes
2	Phone	Medium	256	1875	0.136533	No	18	Yes
3	Phone	Medium	233	1875	0.124267	No	24	Yes
-	-	-	666	1875	0.124267	-	-	-

	count	mean	std	min	25%	50%	75%	max
Claim Amount	200000.0	1120.478840	796.660796	1.000000	245.000000	1390.000000	1844.000000	2299.000000
Category Premium	200000.0	8963.783895	6114.737202	399.000000	1875.000000	14390.000000	14390.000000	14390.000000
Premium/Amount Ratio	200000.0	0.125024	0.034742	0.002506	0.106741	0.125122	0.143155	0.24812
BMI	200000.0	23.007205	3.164976	18.000000	20.000000	23.000000	26.000000	28.00000

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
 ---  -- 
 0   Claim Reason    200000 non-null   object 
 1   Data confidentiality 200000 non-null   object 
 2   Claim Amount     200000 non-null   int64  
 3   Category Premium 200000 non-null   int64  
 4   Premium/Amount Ratio 200000 non-null   float64
 5   Claim Request output 200000 non-null   object 
 6   BMI               200000 non-null   int64  
 7   Churn             200000 non-null   object 
dtypes: float64(1), int64(3), object(4)
memory usage: 12.2+ MB
```

```
df.duplicated().sum()
np.int64(180627)
```

```
df.columns
Index(['Claim Reason', 'Data confidentiality', 'Claim Amount',
       'Category Premium', 'Premium/Amount Ratio', 'Claim Request output',
       'BMI', 'Churn'],
      dtype='object')
```

```
X = df.drop(["Churn"], axis = 1)
y = df["Churn"]
```

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

Double-click (or enter) to edit

```
# Identify categorical columns in X
categorical_cols_X = X.select_dtypes(include='object').columns

# Apply LabelEncoder to each categorical column in X
for col in categorical_cols_X:
    X[col] = le.fit_transform(X[col])

# Apply LabelEncoder to y, assuming it's categorical (like 'Churn')
y = le.fit_transform(y)
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Fit the data (train the model)
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression(random_state=42)
log_reg.fit(X_train, y_train)
log_reg
```

```
* LogisticRegression ⓘ ⓘ
LogisticRegression(random_state=42)
```

```
y_pred = log_reg.predict(X_test)
print(y_pred)
```

```
[1 1 1 ... 1 1 1]
```

```
scoring = {'acc': 'accuracy',
           'prec_macro': 'precision_macro',
           'rec_macro': 'recall_macro',
           'f1_macro': 'f1_macro'}
```

```
scores = cross_validate(log_reg, X_train,
                        y_train, cv=10, scoring=scoring)
scores

{'fit_time': array([2.09866762, 2.43854952, 1.77350831, 1.55538869, 1.79462528,
                   2.18321013, 1.57878375, 1.45682478, 1.5109818 , 1.45313358]),
 'score_time': array([0.04262996, 0.0227015 , 0.00921583, 0.00977325, 0.01884437,
                     0.00997329, 0.01736283, 0.00980544, 0.01272011, 0.01069617]),
 'test_acc': array([0.9841875, 0.9731875, 0.98225 , 0.9856875, 0.9825625, 0.963125 ,
                    0.982 , 0.9810625, 0.966125 , 0.9831875]),
 'test_prec_macro': array([0.98034028, 0.97114904, 0.9781187 , 0.98106812, 0.97822001,
                           0.95711197, 0.97776966, 0.97651466, 0.9643826 , 0.97947354]),
 'test_rec_macro': array([0.98595506, 0.97090582, 0.98406448, 0.98875356, 0.98471499,
                           0.96432425, 0.98390485, 0.98324181, 0.96230396, 0.98461693]),
 'test_f1_macro': array([0.98301908, 0.9710272 , 0.98094578, 0.98466421, 0.98129239,
                        0.96048448, 0.98068148, 0.9796888 , 0.96332628, 0.98193754])}
```

```
import numpy as np

for key in scores:
    if "test" in key:
        print(f"{key}: {np.mean(scores[key]):.3f}")
```

```
test_acc: 0.978
test_prec_macro: 0.974
test_rec_macro: 0.979
test_f1_macro: 0.977
```

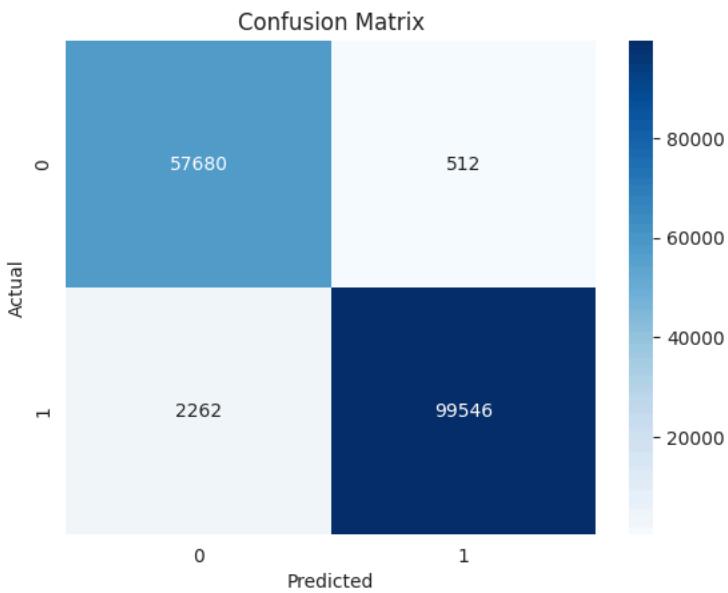
These metrics indicate a highly effective and robust model that performs consistently well across all categories. With a 97.8% accuracy, the model is correct the vast majority of the time, but the high Macro F1 score (0.977) is even more significant; it proves that the model treats all classes equally and isn't simply achieving high accuracy by ignoring minority classes. Furthermore, the negligible gap between

Precision (0.974) and Recall (0.979) demonstrates that the model is unbiased, striking an almost perfect balance between avoiding false alarms (false positives) and missing actual targets (false negatives).

```
from sklearn.metrics import confusion_matrix
yPredTrain = log_reg.predict(X_train) # Make predictions on training data
confusion_matrix(y_train, yPredTrain) # Compare predictions vs real answers

array([[57680, 512],
       [2262, 99546]])
```

```
# plot the confusion matrix
cm = confusion_matrix(y_train, yPredTrain)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



The confusion matrix shows that the model performs extremely well, correctly identifying 57,680 non-churners and 99,546 churners. Only 512 loyal customers were mistakenly flagged as churn risks (false positives), while 2,262 actual churners were missed (false negatives). Both error rates are very low, indicating that the model effectively targets customers who are likely to leave while avoiding unnecessary retention efforts on those who will stay. Overall, the model provides strong predictive accuracy and is highly reliable for supporting insurance churn management decisions.

```
probs = log_reg.predict_proba(X_test)
probs[:,1]

array([0.99966744, 1.          , 1.          , ... , 1.          ,
       0.9999985])
```

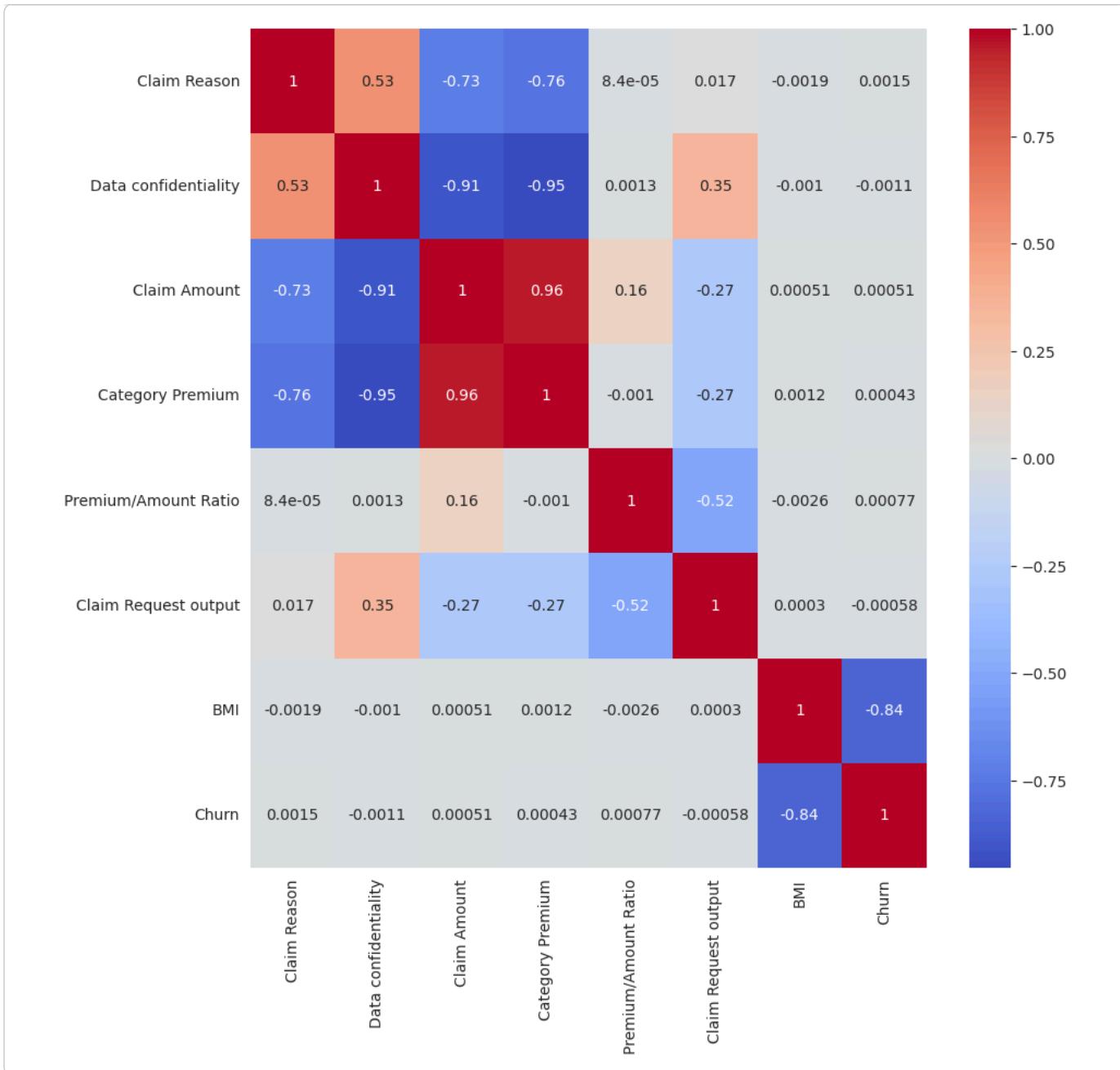
```
# Convert X to DataFrame
X_df = pd.DataFrame(X, columns=log_reg.feature_names_in_)

# Convert y to Series
y_series = pd.Series(y, name="Churn")

# Combine
df1 = pd.concat([X_df, y_series], axis=1)

# Now make correlation matrix
df_corr = df1.corr()

plt.figure(figsize=(10,10))
sns.heatmap(df_corr, annot=True, cmap='coolwarm')
plt.show()
```



The correlation matrix shows that the churn rate has the highest correlation with the BMI. This justifies the selection of BMI for the horizontal axis of the Sigmoid graph.

```
# Plot sigmoid curve
x_range = np.linspace(X_test['BMI'].min(), X_test['BMI'].max(), 300)

# Get all feature names in the order the model was trained on (from X_train)
feature_names = X_train.columns

# Create a dictionary to hold mean values for each feature
mean_values = {col: X_test[col].mean() for col in feature_names}

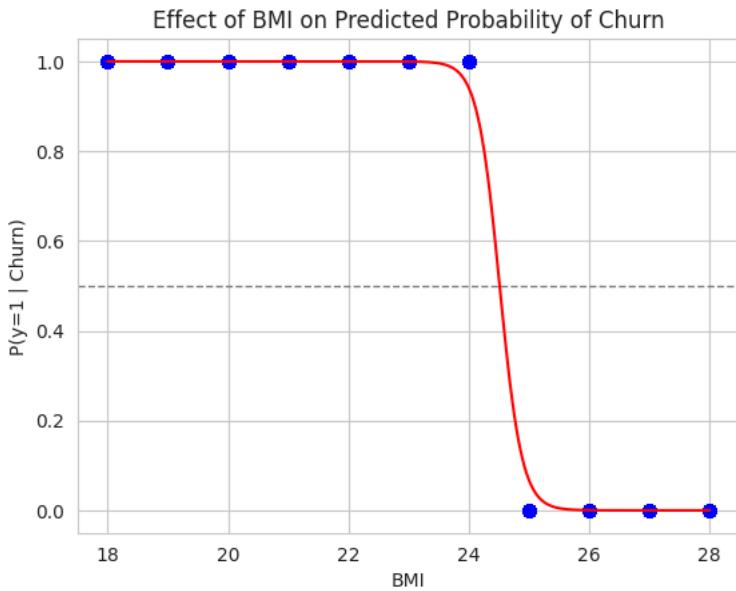
# Create a DataFrame where each column is filled with its mean value, replicated 'len(x_range)' times
# This ensures all columns are present and in the correct order as per feature_names
X_plot = pd.DataFrame([mean_values] * len(x_range), columns=feature_names)

# Now, overwrite the 'BMI' column with the x_range values
X_plot['BMI'] = x_range

y_prob = log_reg.predict_proba(X_plot)[:, 1]

#Plot sigmoid curve
plt.plot(x_range, y_prob, color='red')
```

```
# Scatter points
plt.scatter(X_test['BMI'], y_test, color='blue', alpha=0.4, label='Actual data (0 or 1)', s=40)
# Add a horizontal line at 0.5
plt.axhline(0.5, color='gray', linestyle='--', linewidth=1, label='Decision threshold (0.5)')
plt.xlabel('BMI')
plt.ylabel('P(y=1 | Churn)')
plt.title('Effect of BMI on Predicted Probability of Churn')
plt.show()
```



```
from sklearn import metrics
```

```
# probability of class = 1
probs = log_reg.predict_proba(X_test)[:, 1]
probs

array([0.99966744, 1.          , 1.          , ... , 1.          ,
       0.9999985])
```

```
fpr, tpr, thresholds = metrics.roc_curve(y_test, probs)
```

```
# False positive rate
fpr

array([0.          , 0.          , 0.          , ... , 0.9986929 , 0.99931205,
       1.          ])
```

```
# True positive rate
tpr

array([0.          , 0.04465127, 0.12456802, ... , 1.          ,
       1.          ])
```

```
# Thresholds
thresholds

array([ inf, 1.0000000e+00, 1.0000000e+00, ... ,
       1.24314847e-10, 1.24227757e-10, 1.24140728e-10])
```

```
def auc_score(a, b):
    auc = metrics.roc_auc_score(a, b)
    print("AUC =", auc)
```

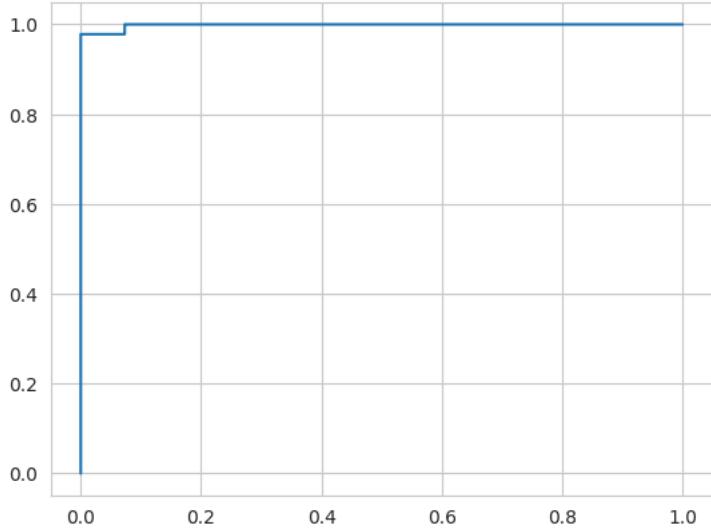
```
auc_score(y_test, probs)
```

```
AUC = 0.9984018844694857
```

An AUC of **0.9984** indicates exceptionally strong model performance, meaning the classifier can distinguish churners from non-churners with 99.84% accuracy across all possible decision thresholds. In practical terms, the model is almost perfectly ranking customers by their churn risk, with minimal overlap between the two groups. This level of AUC is extremely rare in real-world datasets and suggests that the model provides near-flawless separation, making it highly effective for prioritizing retention efforts and supporting insurance decision-making.

```
plt.plot(fpr, tpr)
```

```
[<matplotlib.lines.Line2D at 0x7bdc3734a210>]
```



```
def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0, 1], "k--")
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
```

```
plot_roc_curve(fpr, tpr)
```

