Phase 3 Project

1. Business understanding

Project Goal

To predict whether there is a pattern of customers who will ("soon") stop doing business with SyriaTel, a telecommunications company.

The audience are the telecom business staff whose interest is reducing how much money is lost because of customers who don’t want to stay with the company very long.

Objectives

To determine if there is a predictive pattern of customers who will ("soon") stop doing bussiness with SyriaTel.

2. Data understanding

2.1 Loading the data

In [1]:
```
# importing the necessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import warnings
warnings.filterwarnings("ignore")
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import LabelEncoder
```

In [2]:

```
# Importing the data
df = pd.read_csv('bigml_csv.csv', index_col = 0)
df.head()   # retuns 3333 entries and 20 columns
```

Out[2]:

state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	t mini
KS	128	415	382-4657	no	yes	25	265.1	110	45.07	1
OH	107	415	371-7191	no	yes	26	161.6	123	27.47	1
NJ	137	415	358-1921	no	no	0	243.4	114	41.38	1
OH	84	408	375-9999	yes	no	0	299.4	71	50.90	
OK	75	415	330-6626	yes	no	0	166.7	113	28.34	1

In [3]:

```
# more information about the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3333 entries, KS to TN
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   account length          3333 non-null   int64  
 1   area code               3333 non-null   int64  
 2   phone number            3333 non-null   object 
 3   international plan      3333 non-null   object 
 4   voice mail plan         3333 non-null   object 
 5   number vmail messages   3333 non-null   int64  
 6   total day minutes       3333 non-null   float64
 7   total day calls         3333 non-null   int64  
 8   total day charge        3333 non-null   float64
 9   total eve minutes       3333 non-null   float64
 10  total eve calls         3333 non-null   int64  
 11  total eve charge        3333 non-null   float64
 12  total night minutes     3333 non-null   float64
 13  total night calls       3333 non-null   int64  
 14  total night charge      3333 non-null   float64
 15  total intl minutes      3333 non-null   float64
 16  total intl calls        3333 non-null   int64  
 17  total intl charge       3333 non-null   float64
 18  customer service calls  3333 non-null   int64  
 19  churn                   3333 non-null   bool   
dtypes: bool(1), float64(8), int64(8), object(3)
memory usage: 524.0+ KB
```

3. Data Preparation

In [4]:
```
# format the naming of the columns #  Replace the spaces with '_'
df.rename(columns=lambda x: x.replace(' ', '_'), inplace=True)
```

In [5]:
```
# check the formated column names
print(df.columns)
```

```
Index(['account_length', 'area_code', 'phone_number', 'international_pla
n',
       'voice_mail_plan', 'number_vmail_messages', 'total_day_minutes',
       'total_day_calls', 'total_day_charge', 'total_eve_minutes',
       'total_eve_calls', 'total_eve_charge', 'total_night_minutes',
       'total_night_calls', 'total_night_charge', 'total_intl_minutes',
       'total_intl_calls', 'total_intl_charge', 'customer_service_calls',
       'churn'],
      dtype='object')
```

3.1. Check for missing values

In [6]:
```
# checking for missing values
df.isnull().sum()
```

Out[6]:
```
account_length            0
area_code                 0
phone_number              0
international_plan        0
voice_mail_plan           0
number_vmail_messages     0
total_day_minutes         0
total_day_calls           0
total_day_charge          0
total_eve_minutes         0
total_eve_calls           0
total_eve_charge          0
total_night_minutes       0
total_night_calls         0
total_night_charge        0
total_intl_minutes        0
total_intl_calls          0
total_intl_charge         0
customer_service_calls    0
churn                     0
dtype: int64
```

There are no missing values

In [7]:
```
# Format the columns to remove any spaces from the column lables
df.columns = df.columns.str.strip()
```

In [8]:
```
# print the column names
print(df.columns)
```

```
Index(['account_length', 'area_code', 'phone_number', 'international_pla
n',
       'voice_mail_plan', 'number_vmail_messages', 'total_day_minutes',
       'total_day_calls', 'total_day_charge', 'total_eve_minutes',
       'total_eve_calls', 'total_eve_charge', 'total_night_minutes',
       'total_night_calls', 'total_night_charge', 'total_intl_minutes',
       'total_intl_calls', 'total_intl_charge', 'customer_service_calls',
       'churn'],
      dtype='object')
```

In [9]:
```
# print the unique values of area code
df['area_code'].unique()
```

Out[9]:
```
array([415, 408, 510], dtype=int64)
```

3.2. Defining the features (X) and target (y)

In [10]:
```
# Defining the features (X) and target (y)
X_features = df.drop('churn', axis=1)
y_target = df['churn']
```

In [11]:
```
#convert categorical variables to numerical
# drop-first = True
X_numerical = pd.get_dummies(X_features, drop_first = True)
X_numerical.head(5)
```

Out[11]:

	account_length	area_code	number_vmail_messages	total_day_minutes	total_day_cal
state					
KS	128	415	25	265.1	1
OH	107	415	26	161.6	1:
NJ	137	415	0	243.4	1
OH	84	408	0	299.4	
OK	75	415	0	166.7	1

5 rows × 3350 columns

In [12]:
```
# Encode 'churn'
# print y_encode
y_encode = y_target.astype(int)
y_encode
```

Out[12]:
```
state
KS    0
OH    0
NJ    0
OH    0
OK    0
     ..
AZ    0
WV    0
RI    0
CT    0
TN    0
Name: churn, Length: 3333, dtype: int32
```

In [13]:
```
#encode area code
df['area_code'] = LabelEncoder().fit_transform(df['area_code'])
df['area_code']
```

Out[13]:
```
state
KS    1
OH    1
NJ    1
OH    0
OK    1
     ..
AZ    1
WV    1
RI    2
CT    2
TN    1
Name: area_code, Length: 3333, dtype: int64
```

3.3 Selecting the features for modelling

In [14]:
```
# Selecting the features for medelling
X = X_numerical[['account_length', 'area_code', 'total_day_charge', 'total
y = y_encode
```

In [15]:
```
# print X
print(X)
```

```
       account_length  area_code  total_day_charge  total_eve_charge  \
state
KS                128        415             45.07             16.78
OH                107        415             27.47             16.62
NJ                137        415             41.38             10.30
OH                 84        408             50.90              5.26
OK                 75        415             28.34             12.61
...               ...        ...               ...               ...
AZ                192        415             26.55             18.32
WV                 68        415             39.29             13.04
RI                 28        510             30.74             24.55
CT                184        510             36.35             13.57
TN                 74        415             39.85             22.60

       total_night_charge  total_intl_charge
state
KS                  11.01               2.70
OH                  11.45               3.70
NJ                   7.32               3.29
OH                   8.86               1.78
OK                   8.41               2.73
...                   ...                ...
AZ                  12.56               2.67
WV                   8.61               2.59
RI                   8.64               3.81
CT                   6.26               1.35
TN                  10.86               3.70

[3333 rows x 6 columns]
```

In [16]:
```
#print y
y
```

Out[16]:
```
state
KS    0
OH    0
NJ    0
OH    0
OK    0
     ..
AZ    0
WV    0
RI    0
CT    0
TN    0
Name: churn, Length: 3333, dtype: int32
```

4. Modelling

4.1 Modelling Using statsmodels

In [17]:

```
# fit the baseline Logistic Regression model using statsmodels
# Add a constant (intercept) term to the features
X_constant = sm.add_constant(X)

# Create and fit the Logistic Regression model
logistic_model = sm.Logit(y, X_constant)
results = logistic_model.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.384108
         Iterations 7
```

In [18]:
```
# Print summary
print(results.summary())
```

```
                           Logit Regression Results
==========================================================================
=====
Dep. Variable:                  churn   No. Observations:
3333
Model:                          Logit   Df Residuals:
3326
Method:                           MLE   Df Model:
6
Date:                Sat, 10 May 2025   Pseudo R-squ.:                  0.
07172
Time:                        17:59:59   Log-Likelihood:                 -1
280.2
converged:                       True   LL-Null:                        -1
379.1
Covariance Type:            nonrobust   LLR p-value:                  5.50
6e-40
==========================================================================
=============
                         coef    std err          z      P>|z|      [0.02
5      0.975]
--------------------------------------------------------------------------
-------------
const                 -6.8268      0.696     -9.806      0.000      -8.19
1      -5.462
account_length         0.0012      0.001      0.954      0.340      -0.00
1       0.004
area_code              0.0007      0.001      0.556      0.578      -0.00
2       0.003
total_day_charge       0.0675      0.006     11.632      0.000       0.05
6       0.079
total_eve_charge       0.0662      0.012      5.483      0.000       0.04
3       0.090
total_night_charge     0.0505      0.022      2.265      0.023       0.00
7       0.094
total_intl_charge      0.2935      0.069      4.262      0.000       0.15
9       0.428
==========================================================================
=============
```

Pseudo R-Squared of 0.07172 indicated that the model explains only 7.17% of the variability

In [19]:
```
# Printing the coefficients
print(results.params)
```

```
const                -6.826829
account_length        0.001220
area_code             0.000664
total_day_charge      0.067466
total_eve_charge      0.066206
total_night_charge    0.050466
total_intl_charge     0.293521
dtype: float64
```

The coefficients indicate that total_day_charge, total_eve_charge, total_night_charge, total_intl_charge are significant and influence whether whether one churns or not.

A unit increase in international charge increases the chance of churn by 29%.

4.2. Modelling using scikit-learn

In [20]:
```
# import the necessary library
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score
```

In [21]:
```
# Select the features (X) and target (y)
X = X_numerical[['account_length', 'area_code', 'total_day_charge', 'total
y = y_encode
```

In [22]:
```
# train and split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                                                    random_state=42)
```

In [23]:
```
#view the lengths of the results
print(len(X_train), len(X_test), len(y_train), len(y_test))
```

```
2666 667 2666 667
```

In [24]:
```
# Train and fit model
model2 = LogisticRegression()
results2 = model2.fit(X_train, y_train)
```

In [25]:
```
print(results.summary())
```

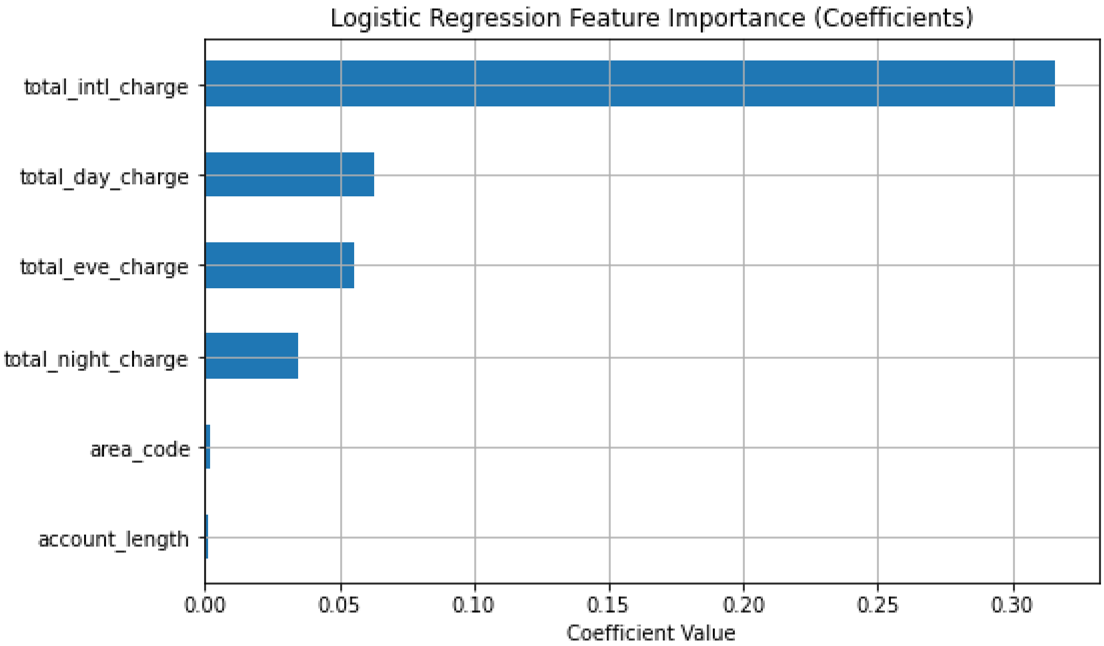
```
                           Logit Regression Results
==============================================================================
=====
Dep. Variable:                  churn   No. Observations:
3333
Model:                          Logit   Df Residuals:
3326
Method:                           MLE   Df Model:
6
Date:                Sat, 10 May 2025   Pseudo R-squ.:                    0.
07172
Time:                        18:00:18   Log-Likelihood:                   -1
280.2
converged:                       True   LL-Null:                          -1
379.1
Covariance Type:            nonrobust   LLR p-value:                    5.50
6e-40
==============================================================================
=============
                        coef    std err          z      P>|z|      [0.02
5      0.975]
------------------------------------------------------------------------------
-------------
const                -6.8268      0.696     -9.806      0.000      -8.19
1      -5.462
account_length        0.0012      0.001      0.954      0.340      -0.00
1       0.004
area_code             0.0007      0.001      0.556      0.578      -0.00
2       0.003
total_day_charge      0.0675      0.006     11.632      0.000       0.05
6       0.079
total_eve_charge      0.0662      0.012      5.483      0.000       0.04
3       0.090
total_night_charge    0.0505      0.022      2.265      0.023       0.00
7       0.094
total_intl_charge     0.2935      0.069      4.262      0.000       0.15
9       0.428
==============================================================================
=============
```

In [26]:
```
# Make predictions on the test data
y_pred = model2.predict(X_test)
```

In [27]:
```
#plotting coeficients vs features

coefs = pd.Series(model2.coef_[0], index=X.columns).sort_values()

plt.figure(figsize=(8, 5))
coefs.plot(kind='barh')
plt.title('Logistic Regression Feature Importance (Coefficients)')
plt.xlabel('Coefficient Value')
plt.grid(True)
plt.show()
```



In [28]:
```
coefs
```

Out[28]:
```
account_length        0.001590
area_code             0.002292
total_night_charge    0.034522
total_eve_charge      0.055797
total_day_charge      0.062950
total_intl_charge     0.316269
dtype: float64
```

The most important feature is the total_intl_charge

A unit increase in international charge increases the chance of churn by 31%.

In [29]:
```
#Evaluation using mse and r squared

mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred) # 0-1: the higher(closer to 1) the better th
print("mse", mse)
print ("r2:", r2)
```

```
mse 0.14992503748125938
r2: -0.16677745513067221
```

A negative r2 indicated that the model is performing poorly

In [30]:

```
# Evaluate the model on training data
train_pred = model2.predict(X_train)
print("Training Accuracy:", accuracy_score(y_train, train_pred)) # checkin
print("Training report")
print(classification_report(y_train, train_pred))

#f1 is a combination of precision and recall
```

```
Training Accuracy: 0.858589647411853
Training report
              precision    recall  f1-score   support

           0       0.86      1.00      0.92      2284
           1       1.00      0.01      0.03       382

    accuracy                           0.86      2666
   macro avg       0.93      0.51      0.47      2666
weighted avg       0.88      0.86      0.80      2666
```

The results indicate that the model accurately predicts whether one will churn or not churn SyriaTel 86% of the time when using the training data

The f1 score for the class 0 is 0.92. However, the f1 score for class 1 is very low 0.02. This is due to the data imbalances, there are more instances for class 0 (2284) compared to class 1(382)

4.3 Confusion Matrix

In [32]:

```
# import library
from sklearn.metrics import confusion_matrix
```

In [33]:

```
# Evaluate on testing data
test_pred = model2.predict(X_test)
print("Testing Accuracy:", accuracy_score(y_test, test_pred)) # checking t
print("Testing report")
print(classification_report(y_test, test_pred))
```

```
Testing Accuracy: 0.8500749625187406
Testing report
              precision    recall  f1-score   support

           0       0.85      1.00      0.92       566
           1       1.00      0.01      0.02       101

    accuracy                           0.85       667
   macro avg       0.92      0.50      0.47       667
weighted avg       0.87      0.85      0.78       667
```

5. Evaluation using ROC and AUC

In [34]:
```
# addressing the data imbalances

from sklearn.metrics import roc_curve, auc

# Scikit-learn's built in roc_curve method returns the fpr, tpr, and thres

# Calculate the probability scores of each of the datapoints:
y_score = model2.fit(X_train, y_train).decision_function(X_test)

fpr, tpr, thresholds = roc_curve(y_test, y_score)
```

In [35]:
```
roc_auc = auc(fpr, tpr)
roc_auc
```

Out[35]:
```
0.7116467830528636
```

In [36]:
```
# Print the AUC
print('AUC: {}'.format(auc(fpr, tpr)))
```

```
AUC: 0.7116467830528636
```

The model has a moderate ability of prediction. The model has a 71.16% chance of predictily correctly the negative and positive classes.

In [37]:

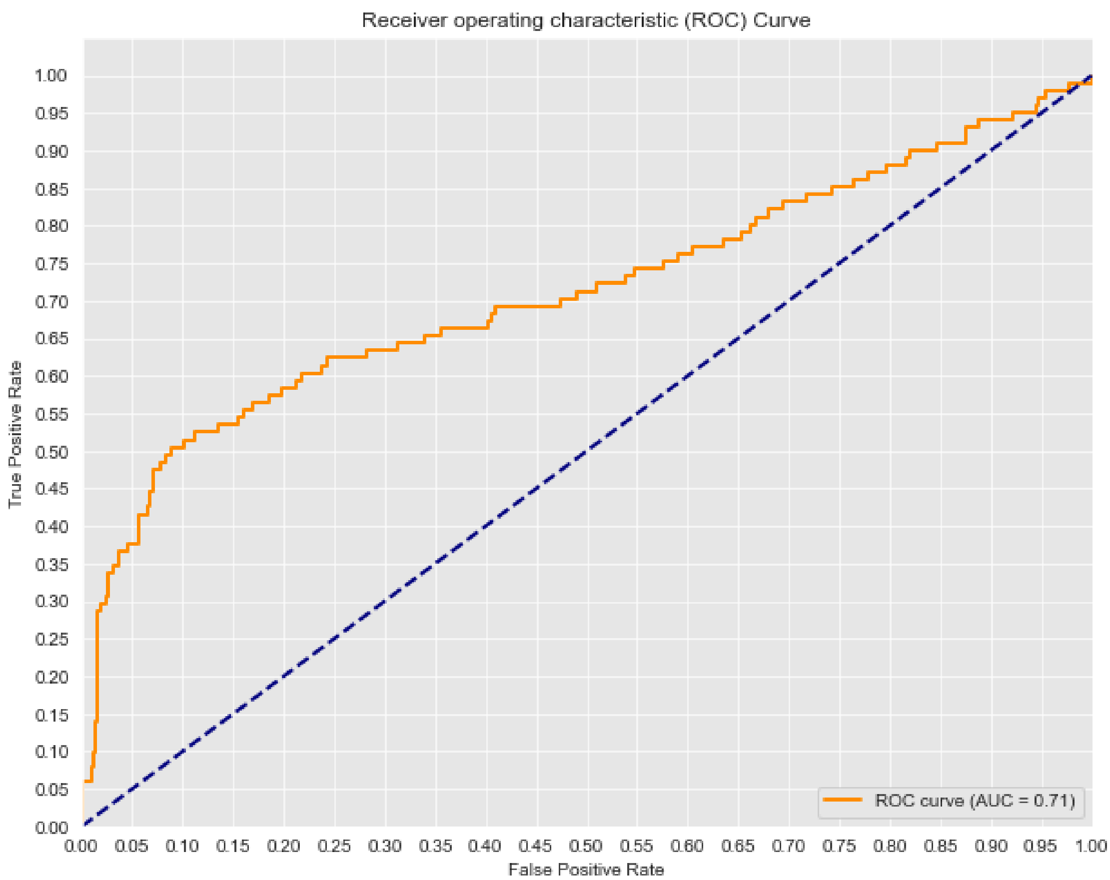
```python
# Visualizing the ROC and AUC

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Seaborn's beautiful styling
sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

print('AUC: {}'.format(auc(fpr, tpr)))
plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
AUC: 0.7116467830528636
```



Scaling the data

In [38]:
```
# import the libraries
from sklearn.preprocessing import MinMaxScaler, PolynomialFeatures, Standa

X = X_numerical[['account_length', 'area_code', 'total_day_charge', 'total
y = y_encode

# train and split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                                                    random_state=42)

# Standardize tha data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# train and fit the model
model3 = LogisticRegression()
results3 = model3.fit(X_train_scaled, y_train)
results3
```

Out[38]:
```
▾ LogisticRegression
LogisticRegression()
```

Hyperparameter Tuning in Decision Trees

In [52]:
```
#import the libraries
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_squared_error
```

In [53]:
```
# define the data
X = X_numerical[['account_length', 'total_day_charge', 'total_eve_charge',
y = df['churn']
```

In [54]:
```
# Train and split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
```

In [55]:
```
# Define the parameter grid to tune the hyperparameters
param_grid = {
    'max_depth': [10, 20, 30, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Instantiating the model
dtree_reg = DecisionTreeRegressor(random_state=1000)

# Perform the grid search
grid_search = GridSearchCV(estimator=dtree_reg, param_grid=param_grid,
                           cv=5, n_jobs=-1, verbose=2, scoring='neg_mean_s
```

In [56]:
```
# Fit the model
grid_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
```

Out[56]:
```
▸ GridSearchCV
▸ estimator: DecisionTreeRegressor
    ▸ DecisionTreeRegressor
```

In [57]:
```
# Get the best estimator from the grid search
best_dtree_reg = grid_search.best_estimator_

# Predict on the test set
y_pred = best_dtree_reg.predict(X_test)

# Calculate Mean Squared Error and RMSE
mse = mean_squared_error(y_test, y_pred)
rmse = mse ** 0.5
```

In [58]:
```
# Get the best hyperparameters
best_params = grid_search.best_params_
print(f"Best parameters: {best_params}")
print(f"Test RMSE: {rmse}")
```

```
Best parameters: {'max_depth': 10, 'min_samples_leaf': 2, 'min_samples_sp
lit': 10}
Test RMSE: 0.33638802926946276
```

RMSE is 0.336 which is better that the baseline model where the RMSE was negative

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GitHub repository link: [https://github.com/PamGodia/dsc-phase3-project-pam (https://github.com/PamGodia/dsc-phase3-project-pam)](https://github.com/PamGodia/dsc-phase3-project-pam)