Week 5 Assignment

Name: Uma Devi Manthapuram

Student ID: 3045896

Course: MSDS_600X40

Professor: Christy Pearson

Data science automation

Using our prepared churn data from week 2:

- use pycaret to find an ML algorithm that performs best on the data
  - Choose a metric you think is best to use for finding the best model; by default, it is accuracy but it could be AUC, precision, recall, etc. The week 3 FTE has some information on these different metrics.
- save the model to disk
- create a Python script/file/module with a function that takes a pandas dataframe as an input and returns the probability of churn for each row in the dataframe
  - your Python file/function should print out the predictions for new data (new_churn_data.csv)
  - the true values for the new data are [1, 0, 0, 1, 0] if you're interested
- test your Python module and function with the new data, new_churn_data.csv
- write a short summary of the process and results at the end of this notebook
- upload this Jupyter Notebook and Python file to a Github repository, and turn in a link to the repository in the week 5 assignment dropbox

Data Loading:

In this assignment, we are using customer churn data prepared in week 2 in which we have converted categorical variables to numeric.

In [1]:

```
import pandas as pd

df = pd.read_csv('/Users/arungajjela/Documents/Uma/MSDS600/MSDS600 Week2/
df
```

Out[1]:

	Unnamed: 0	tenure	PhoneService	Contract	PaymentMethod	MonthlyCharges	TotalCh
customerID							
7590-VHVEG	0	1	0	0	0	3.396185	
5575-GNVDE	1	34	1	1	1	4.042174	18
3668-QPYBK	2	2	1	0	1	3.986202	
7795-CFOCW	3	45	0	1	2	3.744787	18
9237-HQITU	4	2	1	0	0	4.258446	
...	...	...	...	...	...	...	
6840-RESVB	7038	24	1	1	1	4.440296	19
2234-XADUH	7039	72	1	1	3	4.636669	73
4801-JZAZL	7040	11	0	0	0	3.387774	3
8361-LTMKD	7041	4	1	0	1	4.309456	3
3186-AJIEK	7042	66	1	2	2	4.660132	68

7043 rows × 9 columns

In [2]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7043 entries, 7590-VHVEG to 3186-AJIEK
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Unnamed: 0            7043 non-null   int64  
 1   tenure                7043 non-null   int64  
 2   PhoneService          7043 non-null   int64  
 3   Contract              7043 non-null   int64  
 4   PaymentMethod         7043 non-null   int64  
 5   MonthlyCharges        7043 non-null   float64
 6   TotalCharges          7043 non-null   float64
 7   Churn                 7043 non-null   int64  
 8   Total_MonthlyCharges  7043 non-null   float64
dtypes: float64(3), int64(6)
memory usage: 550.2+ KB
```

Using pycaret to find an ML algorithm that performs best on the data:

PyCaret is a Python library that simplifies machine learning for tasks like classification and regression. It acts like an assistant, automating data cleaning, model selection, training, and analysis.

PyCaret can analyze our data and apply different algorithms. It will also compare their performance and help us find the best algorithm for the data.

In [3]:
```
from pycaret.classification import ClassificationExperiment
```

In [4]:
```
automl = ClassificationExperiment()
```

In [5]:
```
automl.setup(df, target='Churn')
```

	Description	Value
0	Session id	3197
1	Target	Churn
2	Target type	Binary
3	Original data shape	(7043, 9)
4	Transformed data shape	(7043, 9)
5	Transformed train set shape	(4930, 9)
6	Transformed test set shape	(2113, 9)
7	Numeric features	8
8	Preprocess	True
9	Imputation type	simple
10	Numeric imputation	mean
11	Categorical imputation	mode
12	Fold Generator	StratifiedKFold
13	Fold Number	10
14	CPU Jobs	-1
15	Use GPU	False
16	Log Experiment	False
17	Experiment Name	clf-default-name
18	USI	eeac

Out[5]:
```
<pycaret.classification.oop.ClassificationExperiment at 0x1506cd790>
```

In [6]:
```
automl
```

Out[6]:
```
<pycaret.classification.oop.ClassificationExperiment at 0x1506cd790>
```

In [7]:
```
best_model = automl.compare_models()
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
gbc	Gradient Boosting Classifier	0.7868	0.8314	0.4579	0.6370	0.5319	0.3989	0.4084	0.1180
ridge	Ridge Classifier	0.7862	0.8155	0.3983	0.6627	0.4965	0.3716	0.3914	0.0120
lr	Logistic Regression	0.7860	0.8256	0.4824	0.6268	0.5443	0.4077	0.4142	0.5670
lda	Linear Discriminant Analysis	0.7850	0.8155	0.4778	0.6261	0.5411	0.4041	0.4109	0.0110
ada	Ada Boost Classifier	0.7838	0.8296	0.4679	0.6242	0.5338	0.3970	0.4046	0.0410
lightgbm	Light Gradient Boosting Machine	0.7822	0.8214	0.4946	0.6109	0.5461	0.4050	0.4092	0.6340
rf	Random Forest Classifier	0.7815	0.8123	0.4771	0.6141	0.5363	0.3965	0.4023	0.0960
et	Extra Trees Classifier	0.7708	0.8044	0.4633	0.5853	0.5166	0.3693	0.3739	0.0940
dummy	Dummy Classifier	0.7347	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0110
dt	Decision Tree Classifier	0.7247	0.6512	0.4946	0.4828	0.4883	0.3002	0.3004	0.0130
nb	Naive Bayes	0.7231	0.7952	0.7217	0.4856	0.5802	0.3853	0.4026	0.0110
knn	K Neighbors Classifier	0.7172	0.6304	0.2646	0.4449	0.3313	0.1667	0.1759	0.2810
qda	Quadratic Discriminant Analysis	0.7067	0.8161	0.7943	0.4690	0.5896	0.3842	0.4168	0.0110
svm	SVM - Linear Kernel	0.6517	0.6950	0.3702	0.3147	0.2571	0.0982	0.1226	0.0140

```
Processing:   0%|          | 0/61 [00:00<?, ?it/s]
```

`best_model = automl.compare_models()` in PyCaret refers to the comparison and select best performing model for machine learning task

From the above result GBC may seem more efficient at most volumes, ultimately the "best model" depends on your specific preferences. Here is a breakdown of things to consider.

Overall Precision vs Specific Class Performance: If overall accuracy is important, GBC might be the best choice. However, if there is a greater need to identify (remember) victimized customers, a Ridge Classifier may be preferred.

Balance between accuracy and recall: If we want to avoid false positives (predict churn when it won't), focus on more accurate images (GBC in this case).

In churn forecasting, a good balance between accuracy, recall and accuracy is often desired. Considering these features and the results presented, both Gradient Boosting Classifier (GBC) and Ridge Classifier (Ridge) can be strong candidates for further research You may want to test their performance on a validation set as it is separately for final decision.

In [8]:
```
best_model
```

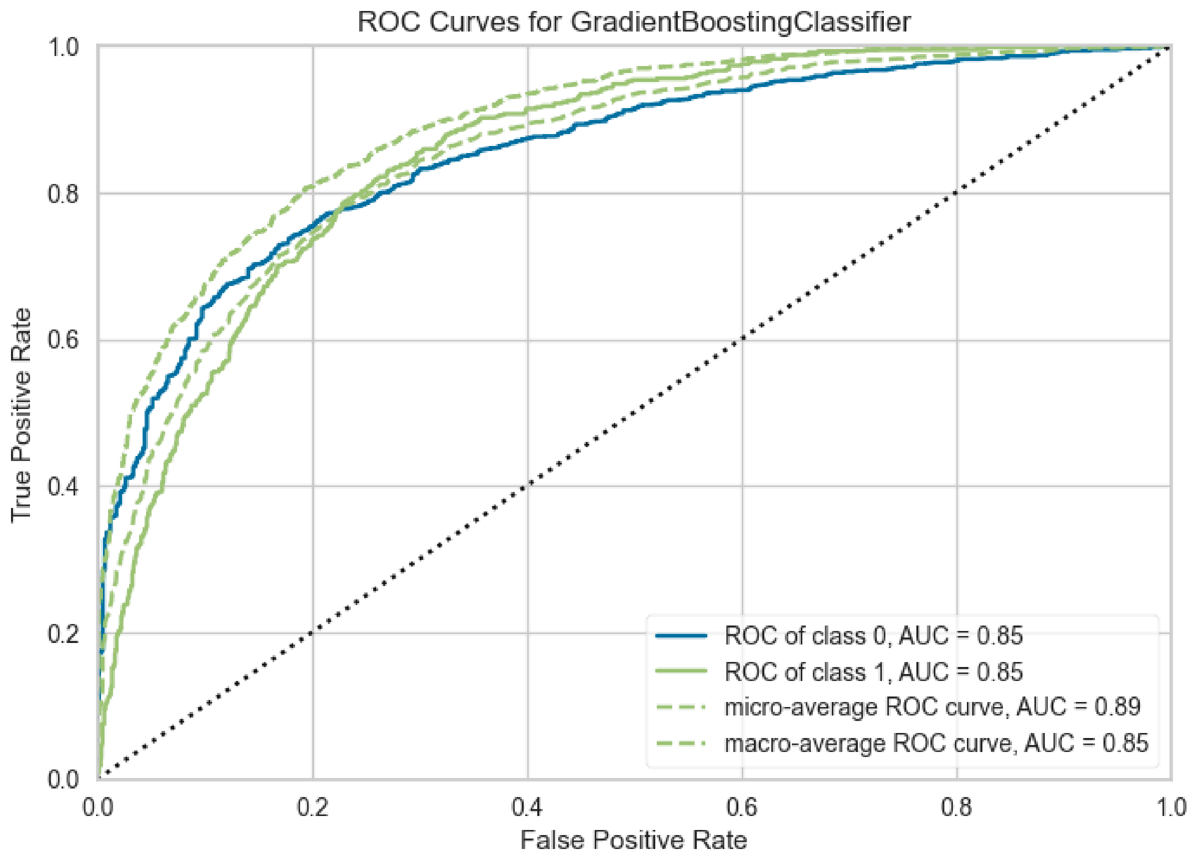
Out[8]:
```
GradientBoostingClassifier(ccp_alpha=0.0, criterion='friedman_mse', ini
t=None,
                           learning_rate=0.1, loss='log_loss', max_dept
h=3,
                           max_features=None, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_samples_leaf=
1,
                           min_samples_split=2, min_weight_fraction_lea
f=0.0,
                           n_estimators=100, n_iter_no_change=None,
                           random_state=3197, subsample=1.0, tol=0.000
1,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [9]:
```
automl.evaluate_model(best_model)
```

```
interactive(children=(ToggleButtons(description='Plot Type:', icons=
('',), options=(('Pipeline Plot', 'pipelin…
```

In [10]:
```
automl.plot_model(best_model)
```

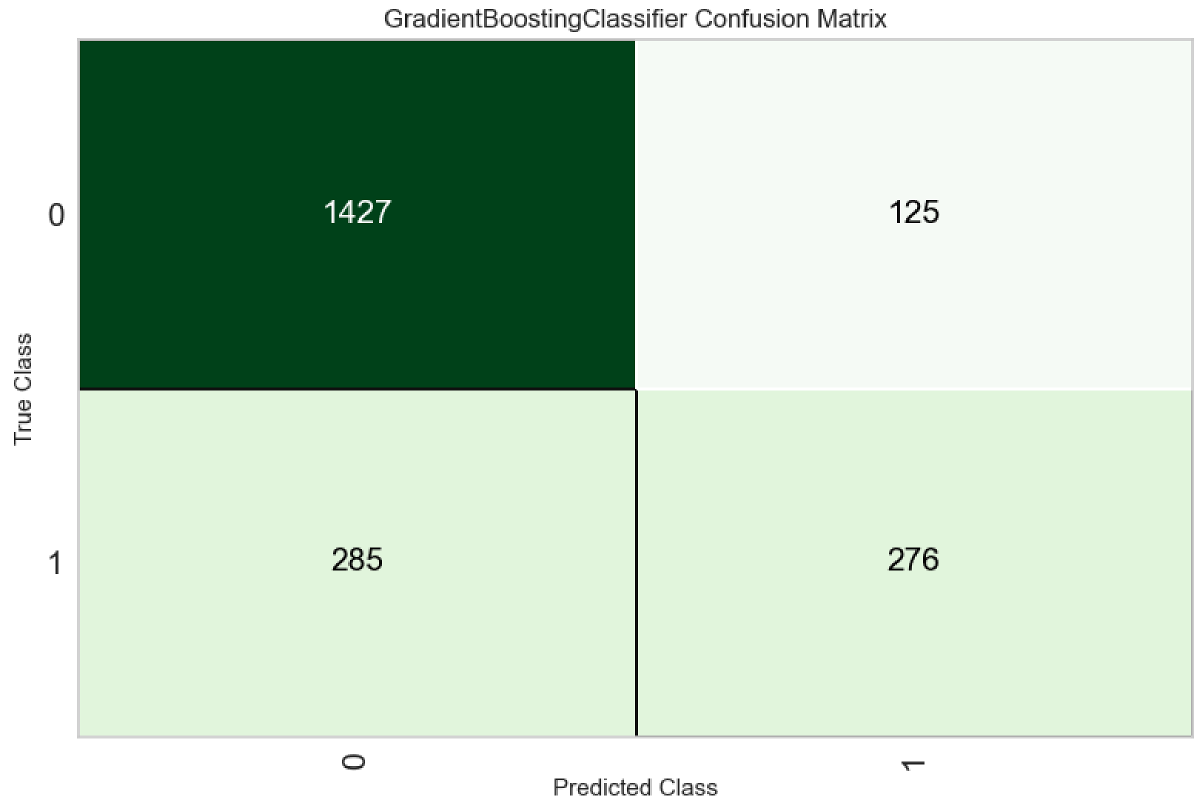


- The ROC Curve for the GradientBoostingClassifier appears above the diagonal line, indicating some ability to discriminate between churned and non-churned clients
- The higher the curve is to the upper left, the better the model performance. Ideally, the curve would hug the left boundary and the top of the graph.

Above plot have multiple AUC values. By comparing these AUC values, you can see if the model performs consistently well across both churned and non-churned customer classes.

Overall, the ROC Curve and AUC values suggest that the LogisticRegression model might have some potential for churn prediction in this dataset

In [11]:
```
automl.plot_model(best_model, plot = 'confusion_matrix')
```



In [12]:
```
df.iloc[-2:-1].shape
```

Out[12]: (1, 9)

In [13]:
```
automl.predict_model(best_model, df.iloc[-2:-1])
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	Gradient Boosting Classifier	1.0000	0	1.0000	1.0000	1.0000	nan	0.0000

Out[13]:

	Unnamed: 0	tenure	PhoneService	Contract	PaymentMethod	MonthlyCharges	TotalCh
customerID							
8361-LTMKD	7041	4	1	0	1	4.309456	306.6

In [14]:
```
predictions = automl.predict_model(best_model, data=df)
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	Gradient Boosting Classifier	0.8194	0.8696	0.5131	0.7260	0.6013	0.4889	0.5012

In [15]:
```
predictions.head()
```

Out[15]:

	Unnamed: 0	tenure	PhoneService	Contract	PaymentMethod	MonthlyCharges	TotalCh
customerID							
7590-VHVEG	0	1	0	0	0	3.396185	29.8
5575-GNVDE	1	34	1	1	1	4.042174	1889.5
3668-QPYBK	2	2	1	0	1	3.986202	108.1
7795-CFOCW	3	45	0	1	2	3.744787	1840.7
9237-HQITU	4	2	1	0	0	4.258446	151.6

Save the model to disk

In [16]:
```
automl.save_model(best_model, 'pycaret_model')
```

```
Transformation Pipeline and Model Successfully Saved
```

Out[16]:
```
(Pipeline(memory=Memory(location=None),
          steps=[('numerical_imputer',
                  TransformerWrapper(exclude=None,
                                     include=['Unnamed: 0', 'tenure',
                                              'PhoneService', 'Contrac
t',
                                              'PaymentMethod', 'Monthly
Charges',
                                              'TotalCharges',
                                              'Total_MonthlyCharges'],
                                     transformer=SimpleImputer(add_indi
cator=False,
                                                               copy=Tru
e,
                                                               fill_val
ue=None,
                                                               keep_emp
ty_features=False,
                                                               missing_
values=nan,
                                                               strate
g...
                                            criterion='friedman_mse',
init=None,
                                            learning_rate=0.1, loss='l
og_loss',
                                            max_depth=3, max_features=
None,
                                            max_leaf_nodes=None,
                                            min_impurity_decrease=0.0,
                                            min_samples_leaf=1,
                                            min_samples_split=2,
                                            min_weight_fraction_leaf=
0.0,
                                            n_estimators=100,
                                            n_iter_no_change=None,
                                            random_state=3197, subsamp
le=1.0,
                                            tol=0.0001, validation_fra
ction=0.1,
                                            verbose=0, warm_start=Fals
e))],
          verbose=False),
 'pycaret_model.pkl')
```

The line `automl.save_model(best_model, 'pycaret_model')` utilizes the save_model function within PyCaret to preserve the chosen "best model" for later use.

- Saving the model makes it persist beyond the current Python session. You can incorporate it later to predict new data without having to retrain the model from scratch.
- The stored model can be predicted to be reused on data sets with similar
- This saves training time for future projects.

- We can share the stored model with others who can use it to make predictions without the need for original data or training codes.

Python script/file/module with a function

In [35]:
```
0.9859
import pandas as pd
from pycaret.classification import ClassificationExperiment

def load_data(filepath):
    """
    Loads diabetes data into a DataFrame from a string filepath.
    """
    return pd.read_csv(filepath)

def make_predictions(df):
    """
    Uses the pycaret best model to make predictions on data in the df da
    """
    classifier = ClassificationExperiment()
    model = classifier.load_model('pycaret_model')
    predictions = classifier.predict_model(model, df)
    churn_prob = predictions["Churn"]  # Assuming single row prediction
    return churn_prob



if __name__ == "__main__":
    df = load_data('/Users/arungajjela/Documents/Uma/MSDS600/MSDS600 Weel
    predictions = make_predictions(df)
    print('predictions:')
    print(predictions)
```

```
Transformation Pipeline and Model Successfully Loaded
predictions:
0       0
1       0
2       1
3       0
4       1
       ..
7038    0
7039    0
7040    0
7041    1
7042    0
Name: Churn, Length: 7043, dtype: int8
```

Analysis ¶

In this assignment, we used customer churn data prepared in week 2 to predict churn using machine learning models. This assignment examines customer churn prediction using PyCaret, a robust machine learning platform. We participate in the process of selecting the best model based on the appropriate metric, saving the selected models, and executing customized Python functions to determine the likelihood of creating new data.

The PyCaret automl function simplifies the model selection process. It trains and tests machine learning models on prepared churn data. By specifying target variables (churn) and ignoring other attributes, we direct the test toward the desired predictive function.

The metric chosen plays an important role. PyCaret trains and compares images, ultimately choosing the one that gets the best accuracy. This gives the selected sample a balance between precision and recall, making it well suited to identifying potential churners in terms of reducing false alarms.

Once PyCaret finds the best model based on the accuracy, we use the save_model function. This function configures the model and saves it to disk with the selected filename. This allows the trained model to be preserved for future use. Instead of retraining the model every time new data becomes available, we can simply load the stored model and use its known patterns to make predictions.

To make predictions about new data easier, we create a custom Python function. This function takes pandas DataFrame (df) as input, which represents additional customer data for churn prediction. These custom functions provide an easy way to integrate the trained model with various applications. We can use it to predict opportunities to create new customer profiles, enabling us to take proactive measures to retain valuable customers.

To check the generalizability of the model, we use a separate data set with additional customer data (which is not used during training). This new data is inserted into a pandas DataFrame, and the function is used. The program returns the predicted churn probabilities for each customer in the new data. Alternatively, we can compare these predicted probabilities with actual churn values (given for this model) to gain insight into the accuracy of the model. A greater correlation between predicted outcomes and actual churn will determine how effective the model is at identifying potential churners.