BA810_Team_12_Customer_Churn

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1 Customer Churn Prediction in Telecom Industry

Team Memebers:

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Colab File Link - https://colab.research.google.com/drive/1p5mb3yonalerpeTzj2VYwh9QxjSYybqc?usp=sharing

1.1 Problem Statement

In this project, we aim to create a model that can effectively predict when customers might churn within a telecommunications company. The cost of acquiring new customers typically outweighs the expenses involved in retaining existing ones, an accurate churn prediction model can help the company allocate resources more effectively. Correctly predicting customers who are likely to churn can significantly benefit the company by reducing the overall costs associated with customer acquisition. This will help decrease customer turnover, improve customer satisfaction, and ensure better retention rates. We will use supervised machine learning techniques to build models that can classify customers as potential churners or non-churners based on their historical usage patterns, service plan features etc. This model will assist the company in identifying customers who are likely to leave in advance, enabling them to take timely actions to retain them.

1.2 Motivation

The telecom industry has a churn rate of 21% following cable (25%), financial/credit (25%), general retail (24%), and online retail (22%). Its churn rate is just a tad lower than fast-moving retail goods. One study even estimated that individual telecom businesses lose up to $65 million because of churn.

Efficient churn analysis involves the early identification and anticipation of customers likely to churn, which leads to promptly addressing issues and enhancing satisfaction. According to some reports, the acquisition cost is 5 times that of the retention cost. The prediction model will help with strategic and efficient resource allocation for acquisition or retention activities. It also helps with optimizing marketing spend through predictive churn analytics. The overall impact extends to minimizing revenue loss through targeted strategies and fostering long-term customer relationships, contributing to sustained business growth.

1.3 Practical Implications

• Targeted Marketing: By segmenting customers based on their churn likelihood, the company can target its marketing campaigns more effectively. High-risk customers can receive campaigns focused on retention. • The insights gained from the model can guide improvements in customer support.

For example, if the model identifies that poor customer service interactions are a significant churn driver, the company can invest in training and resources to address this issue. • Financial Impact: By allocating resources where they are most needed, the company can optimize its budget and efforts. By reducing churn, the company can increase its revenue and profitability. • Customer-Centric Approach: This project reflects a customer-centric approach, which is crucial in today's competitive market. It demonstrates that the company cares about its customers and is willing to invest in retaining them.

2 Data Preview

This dataset will be used for predicting customer churn in telecommunications industry, and it contains categorical varibles and numerical varibles that can be explored and analyzed for predictive modeling and insights. The dataset can be accessed by : https://data.world/bob-wakefield/call-center-data

2.0.1 Data Loading

[ ]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

[ ]:
```python
url = 'https://raw.githubusercontent.com/Parita2442/BA810-Project-Churn-Dataset/
↪main/customer_churn_data.csv'
df = pd.read_csv(url)
df.head()
```

[ ]:
```
   recordID state  account_length  area_code international_plan  \
0         1    HI             101        510                 no
1         2    MT             137        510                 no
2         3    OH             103        408                 no
3         4    NM              99        415                 no
4         5    SC             108        415                 no

  voice_mail_plan  number_vmail_messages  total_day_minutes  total_day_calls  \
0              no                      0               70.9              123
1              no                      0              223.6               86
2             yes                     29              294.7               95
3              no                      0              216.8              123
4              no                      0              197.4               78

   total_day_charge  …  total_eve_charge  total_night_minutes  \
0             12.05  …             18.01                236.0
1             38.01  …             20.81                 94.2
2             50.10  …             20.17                300.3
```

```
3              36.86  ...            10.74                220.6
4              33.56  ...            10.54                204.5

   total_night_calls  total_night_charge  total_intl_minutes  \
0                 73               10.62                10.6
1                 81                4.24                 9.5
2                127               13.51                13.7
3                 82                9.93                15.7
4                107                9.20                 7.7

   total_intl_calls  total_intl_charge  number_customer_service_calls churn  \
0                 3               2.86                              3    no
1                 7               2.57                              0    no
2                 6               3.70                              1    no
3                 2               4.24                              1    no
4                 4               2.08                              2    no

   customer_id
0   23383607.0
1   22550362.0
2   59063354.0
3   25464504.0
4     691824.0

[5 rows x 22 columns]
```

2.0.2 Data Description

[ ]:
```
print("The data has {} number of rows and {} number of columns.".format(df.
 ↪shape[0],df.shape[1]))
```

```
The data has 12892 number of rows and 22 number of columns.
```

2.0.3 Column Description

Column	Description
recordID	Primary key of the record
state	Customers state
account_length	Age of account in months
area_code	area code
international_plan	Whether or not the customer has an international calling plan
voice_mail_plan	Whether or not the customer has a voice mail plan
number_vmail_messages	Number of VM messages customer currently has on the server

Column	Description
total_day_minutes	Customers total usage of day minutes in plan
total_day_calls	Total number of calls customer has made during the day
total_day_charge	How much the customer has been charged for day minutes
total_eve_minutes	Customers total usage of evening minutes in plan
total_eve_calls	Total number of calls customer has made during the evening
total_eve_charge	How much the customer has been charged for evening minutes
total_night_minutes	Customers total usage of night minutes in plan
total_night_calls	Total number of calls customer has made during the night
total_night_charge	How much the customer has been charged for night minutes
total_intl_minutes	Total international minutes
total_intl_calls	Total international calls
total_intl_charge	Total international charges
number_customer_service_calls	How many times the customer has called the IVR system
churn	Customer has churned
customer_id	Enterprise ID of the customer

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12892 entries, 0 to 12891
Data columns (total 22 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   recordID                       12892 non-null  int64
 1   state                          12892 non-null  object
 2   account_length                 12892 non-null  int64
 3   area_code                      12892 non-null  int64
 4   international_plan             12892 non-null  object
 5   voice_mail_plan                12892 non-null  object
 6   number_vmail_messages          12892 non-null  int64
 7   total_day_minutes              12892 non-null  float64
 8   total_day_calls                12892 non-null  int64
 9   total_day_charge               12892 non-null  float64
 10  total_eve_minutes              12892 non-null  float64
 11  total_eve_calls                12892 non-null  int64
 12  total_eve_charge               12892 non-null  float64
```

```
 13  total_night_minutes           12892 non-null  float64
 14  total_night_calls             12892 non-null  int64
 15  total_night_charge            12892 non-null  float64
 16  total_intl_minutes            12892 non-null  float64
 17  total_intl_calls              12892 non-null  int64
 18  total_intl_charge             12892 non-null  float64
 19  number_customer_service_calls 12892 non-null  int64
 20  churn                         12892 non-null  object
 21  customer_id                   12892 non-null  float64
dtypes: float64(9), int64(9), object(4)
memory usage: 2.2+ MB
```

2.0.4 Summary Statistics

[ ]:
```
df.describe()
```

[ ]:
```
          recordID  account_length     area_code  number_vmail_messages  \
count  12892.00000    12892.000000  12892.000000           12892.000000
mean    6446.50000      100.676621    437.133804               7.996665
std     3721.74417       39.806413     42.341820              13.641977
min        1.00000        1.000000    408.000000               0.000000
25%     3223.75000       73.000000    408.000000               0.000000
50%     6446.50000      100.000000    415.000000               0.000000
75%     9669.25000      127.000000    510.000000              19.000000
max    12892.00000      243.000000    510.000000              52.000000

       total_day_minutes  total_day_calls  total_day_charge  \
count       12892.000000     12892.000000      12892.000000
mean          180.162023       100.266599         30.628086
std            54.207056        19.946657          9.215171
min             0.000000         0.000000          0.000000
25%           144.000000        87.000000         24.480000
50%           180.000000       101.000000         30.600000
75%           216.300000       114.000000         36.770000
max           351.500000       165.000000         59.760000

       total_eve_minutes  total_eve_calls  total_eve_charge  \
count       12892.000000     12892.000000      12892.000000
mean          200.711852       100.137139         17.060717
std            50.781851        19.894032          4.316445
min             0.000000         0.000000          0.000000
25%           166.200000        87.000000         14.130000
50%           201.150000       100.000000         17.095000
75%           234.900000       114.000000         19.970000
max           363.700000       170.000000         30.910000

       total_night_minutes  total_night_calls  total_night_charge  \
```

```
count        12892.000000        12892.000000          12892.000000
mean           200.557834          100.038241              9.025192
std             50.632872           19.749714              2.278507
min              0.000000            0.000000              0.000000
25%            167.000000           87.000000              7.520000
50%            200.800000          100.000000              9.040000
75%            235.100000          113.000000             10.580000
max            395.000000          175.000000             17.770000

       total_intl_minutes  total_intl_calls  total_intl_charge  \
count        12892.000000      12892.000000       12892.000000
mean            10.244702          4.467654           2.766584
std              2.782623          2.466493           0.751269
min              0.000000          0.000000           0.000000
25%              8.500000          3.000000           2.300000
50%             10.300000          4.000000           2.780000
75%             12.100000          6.000000           3.270000
max             20.000000         20.000000           5.400000

       number_customer_service_calls   customer_id
count                   12892.000000  1.289200e+04
mean                        1.563683  2.830245e+11
std                         1.310606  3.205835e+13
min                         0.000000  3.400000e+01
25%                         1.000000  2.409909e+07
50%                         1.000000  3.219535e+07
75%                         2.000000  5.535319e+07
max                         9.000000  3.640000e+15
```

[ ]:
```
df.describe(include=object)
```

[ ]:
```
        state international_plan voice_mail_plan  churn
count   12892              12892           12892  12892
unique     51                  2               2      2
top        WV                 no              no     no
freq      402              11651            9372  11069
```

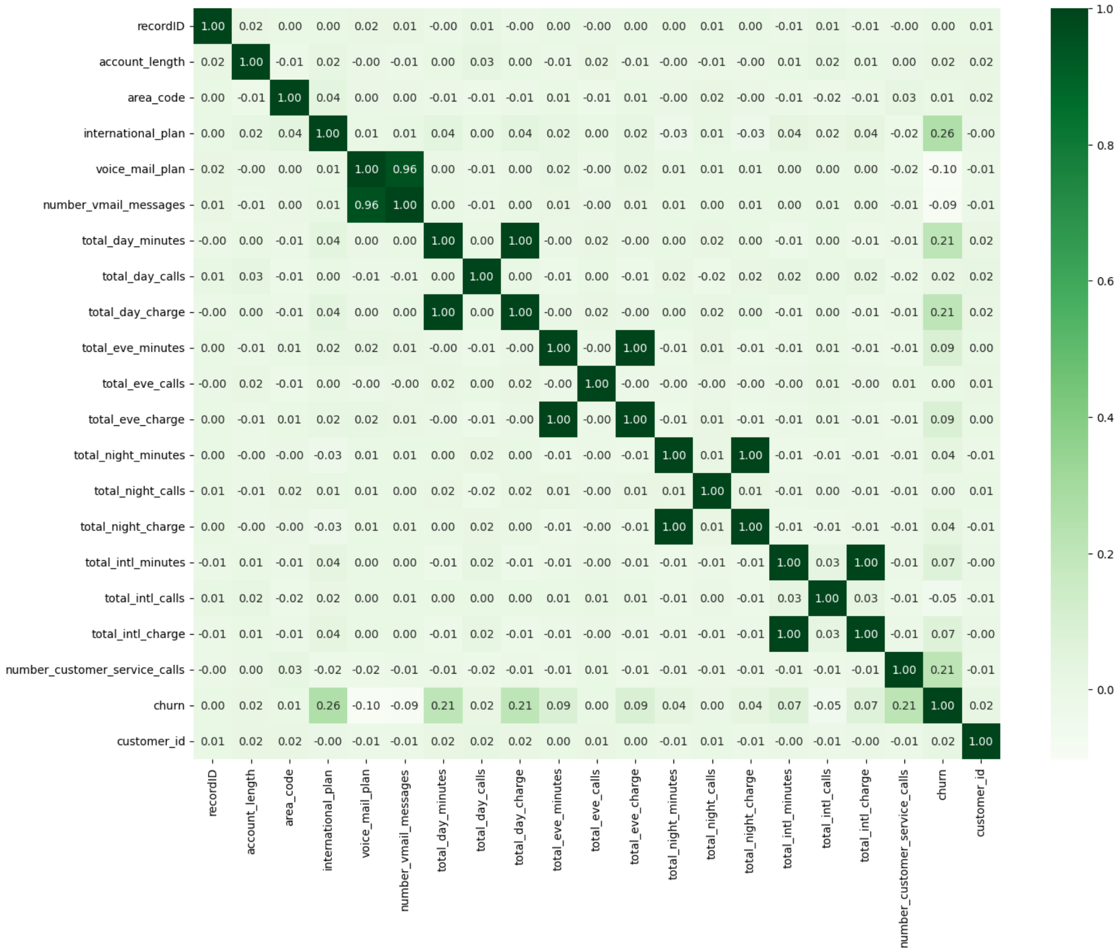
3 Data Exploration

[ ]:
```
df.dropna(inplace=True)
df['international_plan'] = df['international_plan'].map({'yes': 1, 'no': 0})
df['voice_mail_plan'] = df['voice_mail_plan'].map({'yes': 1, 'no': 0})
df['churn'] = df['churn'].map({'yes': 1, 'no': 0}).astype(int)
```

Mapping the dataset and converting the string ‘Yes’ and ‘No’ to numeric data type - 1 and 0 respectively, for prediction and analysis functions.

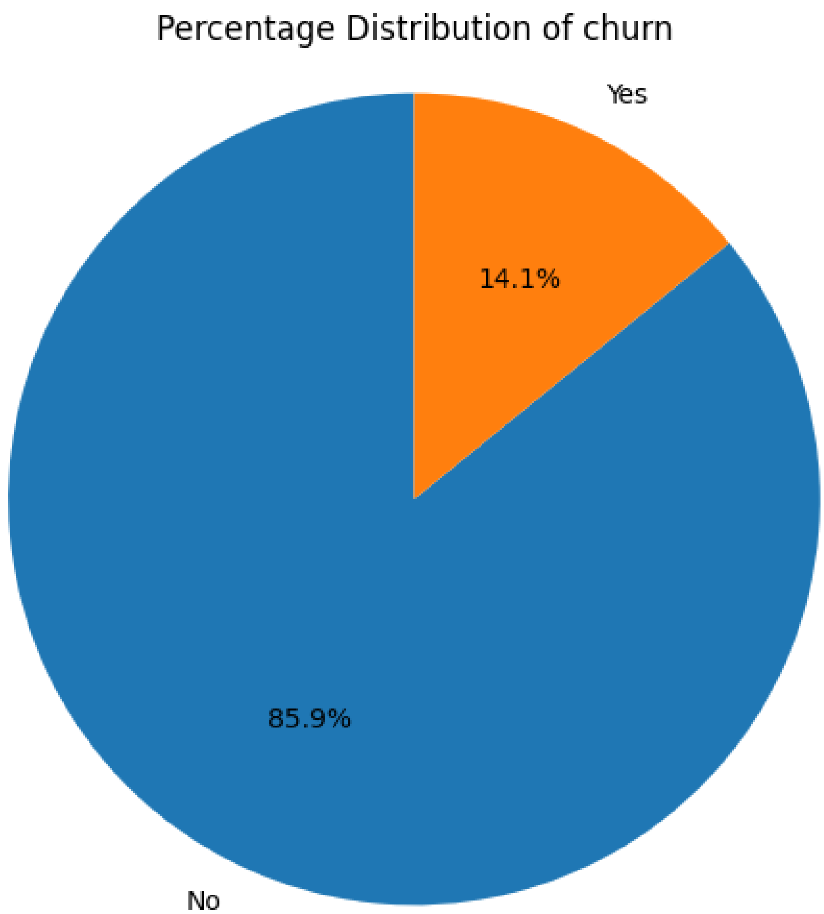
```
[ ]: plt.figure(figsize = (16,12))
     correlations = df.corr()
     sns.heatmap(correlations,annot=True,cmap="Greens",fmt=".2f" )
     plt.show()
```

```
<ipython-input-8-0025cc774a3c>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  correlations = df.corr()
```




```
[ ]: import matplotlib.pyplot as plt

     chun_counts = df['churn'].value_counts()

     plt.figure(figsize=(6, 6))
     plt.pie(chun_counts, labels=['No','Yes'], autopct='%1.1f%%', startangle=90)
     plt.title('Percentage Distribution of churn')
```

```
plt.axis('equal');
```



As we can see a high class imbalance in the churn distribution, we take balanced accuracy as a scoring measure instead of accuracy score.

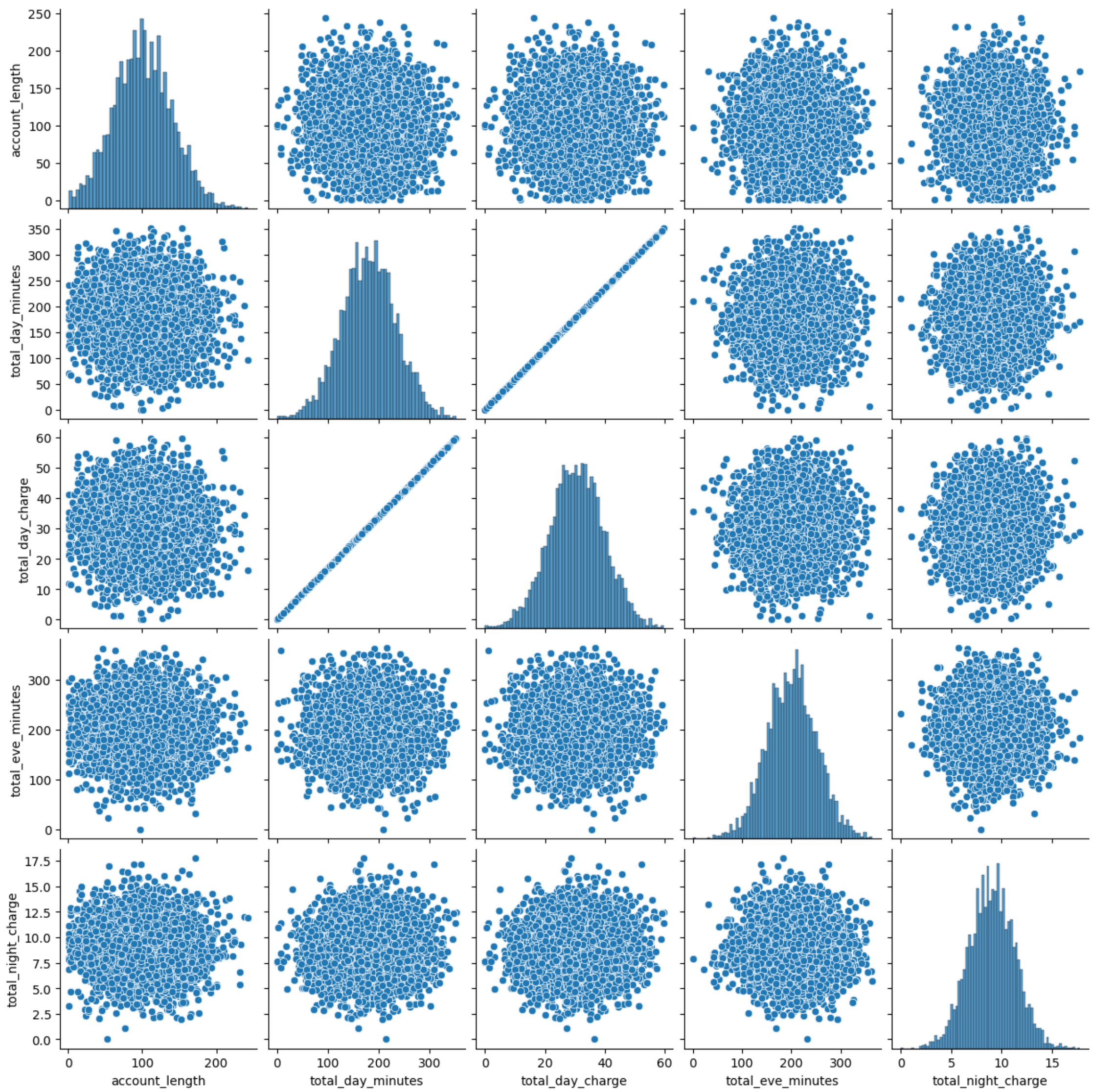
[ ]:
```
def dataoveriew(df, message):
    print(f'{message}:\n')
    print("Rows:", df.shape[0])
    print("\nNumber of features:", df.shape[1])
    print("\nFeatures:")
    print(df.columns.tolist())
    print("\nMissing values:", df.isnull().sum().values.sum())
    print("\nUnique values:")
    print(df.nunique())
dataoveriew(df, 'Overiew of the dataset')
```

```
Overiew of the dataset:
```

```
Rows: 12892

Number of features: 22

Features:
['recordID', 'state', 'account_length', 'area_code', 'international_plan',
'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', 'number_customer_service_calls', 'churn', 'customer_id']

Missing values: 0

Unique values:
recordID                         12892
state                               51
account_length                     218
area_code                            3
international_plan                   2
voice_mail_plan                      2
number_vmail_messages               48
total_day_minutes                 1961
total_day_calls                    123
total_day_charge                  1961
total_eve_minutes                 1879
total_eve_calls                    126
total_eve_charge                  1659
total_night_minutes               1853
total_night_calls                  131
total_night_charge                1028
total_intl_minutes                 170
total_intl_calls                    21
total_intl_charge                  170
number_customer_service_calls       10
churn                                2
customer_id                      12892
dtype: int64
```

[ ]:

```
numeric_df = df[['account_length','total_day_minutes','total_day_charge',␣
↪'total_eve_minutes', 'total_night_charge']]
sns.pairplot(numeric_df);
```



4 Data Preprocessing

```
[ ]: # created and kept a copy of the original dataframe in case needed in the future.
data = df.copy()
```

```
[ ]: # change international_plan, voice_mail_plan, churn to categories - change yes no to 0 & 1
df['international_plan']=df['international_plan'].astype('category')
df['voice_mail_plan']=        df['voice_mail_plan'].astype('category')
df['churn'] = df['churn'].astype('category')
df['area_code'] = df['area_code'].astype('category')
```

[ ]:
```
# drop Record ID and customer ID - unique values , total charges- rates same␣
↪based on usage
df.drop(columns=['recordID','customer_id',␣
↪'state','total_day_charge','total_eve_charge',
                 'total_night_charge','total_intl_charge'],inplace=True)
```

'Customer_id' and 'recordID' are dropped because they are unique and do not hold any importance in the models. Looking at the correlation matrix, the 'total charges' columns are highly correlated to the 'call minutes' columns (as total charges is a product of minutes and rate), we drop them as it affects the target variable - churn in the same way.

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12892 entries, 0 to 12891
Data columns (total 15 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   account_length                 12892 non-null  int64
 1   area_code                      12892 non-null  category
 2   international_plan             12892 non-null  category
 3   voice_mail_plan                12892 non-null  category
 4   number_vmail_messages          12892 non-null  int64
 5   total_day_minutes              12892 non-null  float64
 6   total_day_calls                12892 non-null  int64
 7   total_eve_minutes              12892 non-null  float64
 8   total_eve_calls                12892 non-null  int64
 9   total_night_minutes            12892 non-null  float64
 10  total_night_calls              12892 non-null  int64
 11  total_intl_minutes             12892 non-null  float64
 12  total_intl_calls               12892 non-null  int64
 13  number_customer_service_calls  12892 non-null  int64
 14  churn                          12892 non-null  category
dtypes: category(4), float64(4), int64(7)
memory usage: 1.1 MB
```

As the dataset is highly imbalanced, we use the stratification technique for the train test split, so a more accurate model prediction is achieved.

4.0.1 Stratified Train Test Split

[ ]:
```
from sklearn.model_selection import train_test_split
X=df.drop(columns='churn')
y=df.churn
X_train_all_features,X_test_all_features,y_train_all_features,y_test_all_features␣
↪= train_test_split(X,y,test_size=0.20,stratify=y,random_state=12)
X_train_all_features.shape, X_test_all_features.shape, y_train_all_features.
↪shape, y_test_all_features.shape
```

[ ]: ((10313, 14), (2579, 14), (10313,), (2579,))

4.0.2 Preprocessing Pipeline

[ ]:
```
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer, make_column_selector

from sklearn import set_config
set_config(display='diagram')

num_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy='median')),('standard␣
 ↪scaler',StandardScaler())
    ])
cat_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy='most_frequent')),
        ('cat_encoder', OneHotEncoder(drop="first"))
    ])

prep_pipeline = ColumnTransformer([
    ('num', num_pipeline, make_column_selector(dtype_include=np.number)),
    ('cat', cat_pipeline, make_column_selector(dtype_include='category'))
])

prep_pipeline
```

[ ]:
```
ColumnTransformer(transformers=[('num',
                                 Pipeline(steps=[('imputer',
SimpleImputer(strategy='median')),
                                                 ('standard scaler',
                                                  StandardScaler())]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7a730f745c60>),
                                ('cat',
                                 Pipeline(steps=[('imputer',
SimpleImputer(strategy='most_frequent')),
                                                 ('cat_encoder',
OneHotEncoder(drop='first'))]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7a730f4427a0>)])
```

[ ]:

4.0.3 Feature Selection - Logistic Regression L1

[ ]:
```
from sklearn.feature_selection import SelectFromModel
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline

lr = LogisticRegression(penalty='l1', solver='liblinear')

select_from_model = SelectFromModel(lr)

model_pipe = Pipeline([
    ('prep', prep_pipeline),
    ('select', select_from_model),
    ('model', lr)])

model_pipe
```

[ ]:
```
Pipeline(steps=[('prep',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='median')),
                                                                  ('standard '
                                                                   'scaler',
StandardScaler())]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7a730f745c60>),
                                                 ('cat',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='most_frequent')),
('cat_encoder',
OneHotEncoder(drop='first'))]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7a730f4427a0>)])),
                ('select',
                 SelectFromModel(estimator=LogisticRegression(penalty='l1',
solver='liblinear'))),
                ('model',
                 LogisticRegression(penalty='l1', solver='liblinear'))])
```

[ ]:
```
#Grid Search Using L1 regularization
from sklearn.model_selection import GridSearchCV

param_grid = {
    'select__estimator__C': [0.001, 0.01, 0.1, 1, 10, 100],
    'select__threshold': ['mean', 'median']
}
```

```
grid_search = GridSearchCV(model_pipe, param_grid, cv=5,␣
↪scoring='balanced_accuracy')
grid_search.fit(X_train_all_features, y_train_all_features)

best_params = grid_search.best_params_
print("Best parameters:", best_params)

cv_res = pd.DataFrame(grid_search.cv_results_)
cv_res.sort_values(by="mean_test_score", ascending=False, inplace=True)
display(cv_res.filter(regex='(^param_|mean_test_score)', axis=1))

best_model = grid_search.best_estimator_

selected_features = best_model['prep'].
↪get_feature_names_out()[best_model['select'].get_support()]
print(f'The selected features are {selected_features}')
```

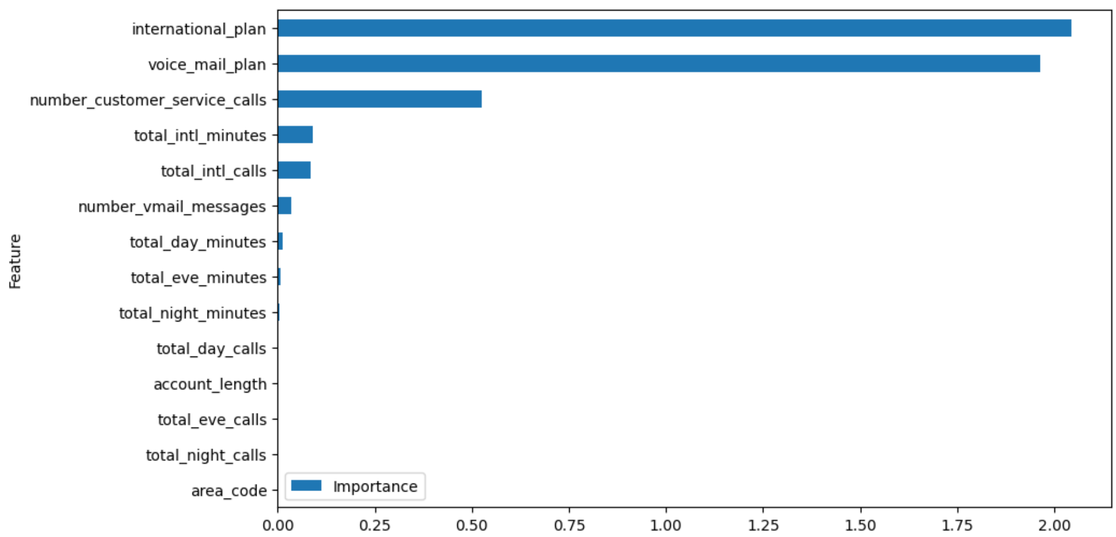
```
Best parameters: {'select__estimator__C': 0.1, 'select__threshold': 'median'}
```

	param_select__estimator__C	param_select__threshold	mean_test_score
5	0.1	median	0.594585
3	0.01	median	0.593777
0	0.001	mean	0.592235
1	0.001	median	0.592235
7	1	median	0.589138
9	10	median	0.589138
11	100	median	0.589138
2	0.01	mean	0.568336
4	0.1	mean	0.568166
6	1	mean	0.566509
8	10	mean	0.565599
10	100	mean	0.565599

```
The selected features are ['num__total_day_minutes' 'num__total_eve_minutes'
 'num__total_night_minutes' 'num__total_intl_minutes'
 'num__total_intl_calls' 'num__number_customer_service_calls'
 'cat__international_plan_1' 'cat__voice_mail_plan_1']
```

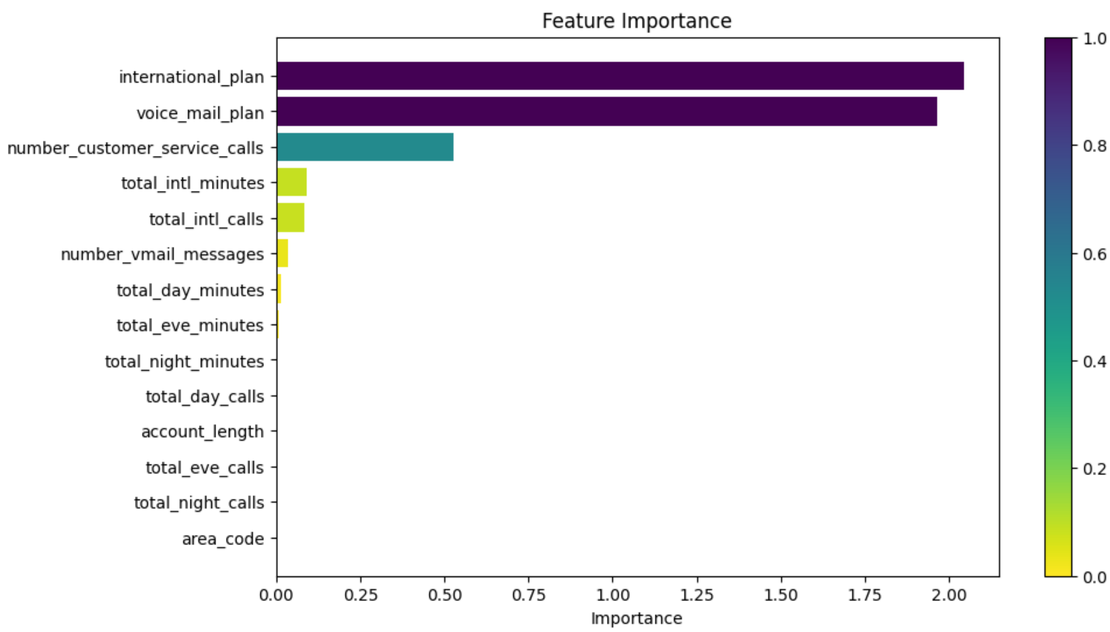
[ ]:
```
# Feature Importance
lr.fit(X_train_all_features, y_train_all_features)
feature_importance = pd.DataFrame({'Feature': X.columns, 'Importance': np.
↪abs(lr.coef_[0])})
feature_importance = feature_importance.sort_values('Importance',␣
↪ascending=True)
feature_importance.plot(x='Feature', y='Importance', kind='barh', figsize=(10,␣
↪6))
```

[ ]: <Axes: ylabel='Feature'>



[ ]:
```python
fig, ax = plt.subplots(figsize=(10, 6))
bars = ax.barh(feature_importance['Feature'], feature_importance['Importance'],␣
↪color=plt.cm.get_cmap('viridis_r')(feature_importance['Importance']))

cbar = plt.colorbar(plt.cm.ScalarMappable(cmap='viridis_r'), ax=ax)

ax.set_xlabel('Importance')
ax.set_title('Feature Importance')

plt.show()
```

```
<ipython-input-19-05b557d4c8e6>:2: MatplotlibDeprecationWarning: The get_cmap
function was deprecated in Matplotlib 3.7 and will be removed two minor releases
later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  bars = ax.barh(feature_importance['Feature'],
feature_importance['Importance'],
color=plt.cm.get_cmap('viridis_r')(feature_importance['Importance']))
```




```
[ ]: selected_features = ['total_day_minutes', 'total_eve_minutes',
      'total_night_minutes', 'total_intl_minutes',
      'total_intl_calls', 'number_customer_service_calls',
      'international_plan', 'voice_mail_plan']
     X_train = X_train_all_features[selected_features]
     y_train = y_train_all_features
     X_test= X_test_all_features[selected_features]
     y_test = y_test_all_features
```

Lasso shrinks the less important feature's coefficient to zero thus, removing some features altogether. So, this works well for feature selection in case we have a huge number of features. This is why we used L1 with logistic regression to find the best features for our model.

4.0.4 Cost Function

```
[ ]: from sklearn.metrics import make_scorer, confusion_matrix
     def default_cost(y_true, y_pred):
       cm = confusion_matrix(y_true, y_pred)
       return cm[1,0] * 34 + cm[0,1] * 7
       # cost of 34 for false negative and 7 for false positives

     cost_scorer = make_scorer(default_cost)
```

The industry average for Monthly revenue per customer in the telecom industry is USD 62 and the gross margin is 55%. Studies show that the acquisition cost is 5 times that of the retention cost in the industry. A telecom company will have to incur costs like - customer acquisition and retention costs. When the model predicts correctly, it helps the company efficiently allocate its resources towards the acquisition and retention activities.

When the model predicts that a customer will not churn but in actuality, change their service provider (False Negative), the company loses out on the revenue that that customer would have generated (64*0.55 = USD 34). Whereas, when the model predicts that a customer will churn but instead, he doesn't (False Positive) - the company wrongly incurs retention costs (Acquistion cost/ 5 = USD 7) to try and keep the customer with their telecom plan.

4.0.5 Score Function

[ ]:
```
from sklearn.metrics import accuracy_score, balanced_accuracy_score, f1_score,␣
 ↪precision_score, recall_score, confusion_matrix, ConfusionMatrixDisplay

def print_scores(y_test, y_pred):
  cmd = ConfusionMatrixDisplay.from_predictions(y_test, y_pred, cmap=plt.cm.
 ↪Blues, colorbar=False)
  accuracy = accuracy_score(y_test, y_pred)
  balanced_accuracy = balanced_accuracy_score(y_test, y_pred)
  print(f'Accuracy = {accuracy:.4f}, Balanced Accuracy = {balanced_accuracy:.
 ↪4f}')
  precision = precision_score(y_test, y_pred)
  recall = recall_score(y_test, y_pred)
  f1 = f1_score(y_test, y_pred)
  print(f'Precision = {precision:.4f}, Recall = {recall:.4f}, F1-score = {f1:.
 ↪4f}')
  cost = default_cost(y_test, y_pred)
  print(f'Cost = {cost}')
```

5 Model Building

5.1 1. Logistic Regression

[ ]:
```
lr_pipe = Pipeline([
    ('prep', prep_pipeline),
    ('model', lr)])

lr_pipe
```

[ ]:
```
Pipeline(steps=[('prep',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='median')),
                                                                  ('standard '
                                                                   'scaler',
StandardScaler())]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7a730f745c60>),
```

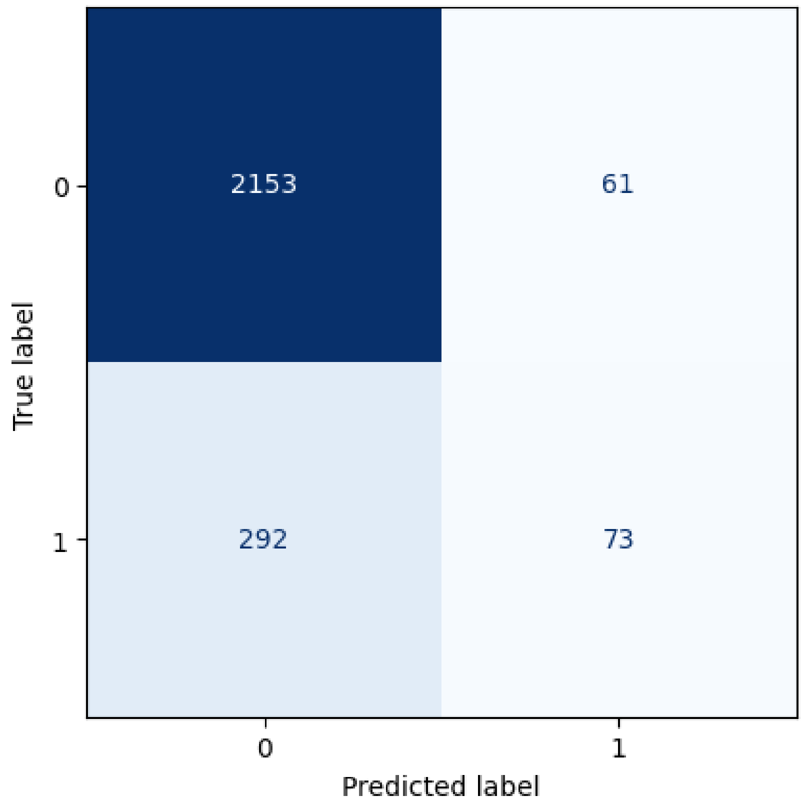
```
                                                  ('cat',
                                                   Pipeline(steps=[('imputer',
SimpleImputer(strategy='most_frequent')),
('cat_encoder',
OneHotEncoder(drop='first'))]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7a730f4427a0>)])),
                ('model',
                 LogisticRegression(penalty='l1', solver='liblinear'))])
```

5.1.1 L1 Scores

[ ]:
```python
from sklearn.metrics import accuracy_score, classification_report,
 ↪balanced_accuracy_score
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

logreg = LogisticRegression(penalty='l1', solver='saga', random_state=42)

logreg.fit(X_train_scaled, y_train)

y_pred = logreg.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)
balanced_accuracy = balanced_accuracy_score(y_test, y_pred)

print(f'Accuracy: {accuracy:.4f}')
print('Classification Report:\n', classification_rep)
print(f'Balanced Accuracy of Logistic Regression with L1: {balanced_accuracy}')
print_scores(y_test, y_pred)
```

```
Accuracy: 0.8631
Classification Report:
               precision    recall  f1-score   support

           0       0.88      0.97      0.92      2214
           1       0.54      0.20      0.29       365

    accuracy                           0.86      2579
   macro avg       0.71      0.59      0.61      2579
weighted avg       0.83      0.86      0.83      2579

Balanced Accuracy of Logistic Regression with L1: 0.5862240289069558
```

```
Accuracy = 0.8631, Balanced Accuracy = 0.5862
Precision = 0.5448, Recall = 0.2000, F1-score = 0.2926
Cost = 10355
```



The Logistic Regression model with L1 regularization exhibits a high overall accuracy of 86.31%, indicating strong performance on the majority class. The Balanced Accuracy of approximately 58.62% suggests a reasonable ability to make accurate predictions across both classes, considering class imbalance. The relatively low recall indicates that the model might not effectively capture all actual positive instances. The cost associated with misclassifications is 10,355, highlighting the economic impact of prediction errors.

5.1.2 Grid Search with L2

[ ]:
```
# Grid Search using L2 regularization

lr_l2 = LogisticRegression(penalty='l2', solver='liblinear')

lr_l2_pipe = Pipeline([
    ('prep', prep_pipeline),
    ('model', lr_l2 )
])
```

```python
param_grid = {
    'model__C': [0.001, 0.01, 0.1, 1, 10, 100],
    #'model__threshold': ['mean', 'median']
}

grid_search = GridSearchCV(lr_l2_pipe, param_grid, cv=5,␣
 ↪scoring='balanced_accuracy')
grid_search.fit(X_train, y_train)

best_params = grid_search.best_params_
print("Best parameters:", best_params)

cv_res = pd.DataFrame(grid_search.cv_results_)
cv_res.sort_values(by="mean_test_score", ascending=False, inplace=True)
display(cv_res.filter(regex='(^param_|mean_test_score)', axis=1))
```

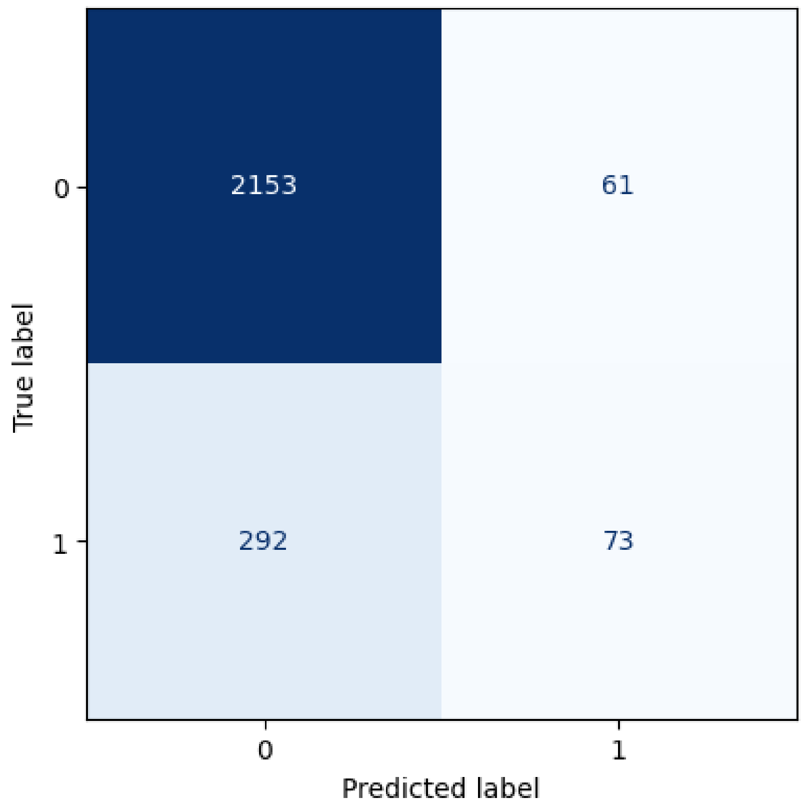
```
Best parameters: {'model__C': 10}
```

	param_model__C	mean_test_score
4	10	0.595158
5	100	0.595158
3	1	0.594411
2	0.1	0.585354
1	0.01	0.548520
0	0.001	0.508295

5.1.3 L2 Scores

[ ]:
```python
y_pred= grid_search.best_estimator_.predict(X_test)
print_scores(y_test, y_pred)
```

```
Accuracy = 0.8631, Balanced Accuracy = 0.5862
Precision = 0.5448, Recall = 0.2000, F1-score = 0.2926
Cost = 10355
```



The Logistic Regression model with L2 regularization, tuned using grid search, presents an accuracy of 86.31% and a balanced accuracy of 58.62%. The use of L2 regularization helps control overfitting by penalizing large coefficients. It's noteworthy that while the accuracy is high, the balanced accuracy is not significantly higher than that achieved with L1 regularization. This suggests that in the context of the imbalanced dataset, the benefits of L2 regularization in improving balanced accuracy might be limited.

[ ]:
```
!pip install scikit-optimize
```

```
Collecting scikit-optimize
  Downloading scikit_optimize-0.9.0-py2.py3-none-any.whl (100 kB)
                           100.3/100.3

kB 2.2 MB/s eta 0:00:00
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from scikit-optimize) (1.3.2)
Collecting pyaml>=16.9 (from scikit-optimize)
  Downloading pyaml-23.9.7-py3-none-any.whl (23 kB)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (1.23.5)
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (1.11.4)
```

```
Requirement already satisfied: scikit-learn>=0.20.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-optimize) (1.2.2)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.10/dist-packages
(from pyaml>=16.9->scikit-optimize) (6.0.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0->scikit-
optimize) (3.2.0)
Installing collected packages: pyaml, scikit-optimize
Successfully installed pyaml-23.9.7 scikit-optimize-0.9.0
```

5.1.4 Bayesian Optimization with L1

[ ]:
```
# Bayesian Optimization with L1
from skopt import BayesSearchCV

param_space = {
    'model__C': (0.001, 1000.0, 'log-uniform')
}

bayes_search_1 = BayesSearchCV(
    lr_pipe,
    param_space,
    n_iter=50,
    cv=5,
    scoring='balanced_accuracy',
    random_state=42
)

bayes_search_1.fit(X_train, y_train)

cv_res = pd.DataFrame(bayes_search_1.cv_results_)
cv_res.sort_values(by="mean_test_score", ascending=False, inplace=True)
display(cv_res.filter(regex='(^param_|mean_test_score)', axis=1))
```

```
/usr/local/lib/python3.10/dist-packages/skopt/optimizer/optimizer.py:449:
UserWarning: The objective has been evaluated at this point before.
  warnings.warn("The objective has been evaluated "
```

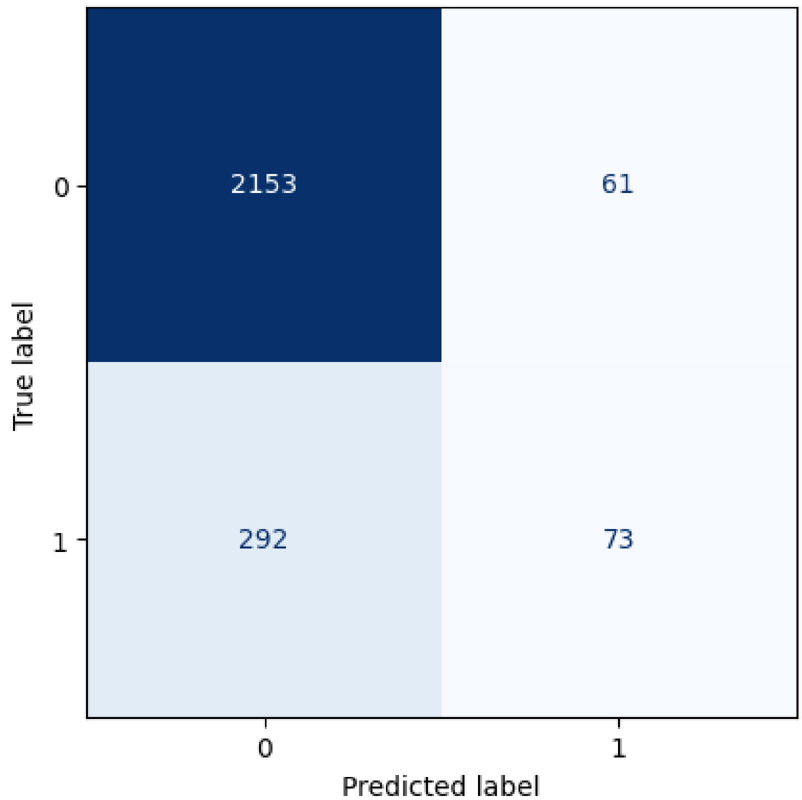
	param_model__C	mean_test_score
25	767.513693	0.595158
30	13.717307	0.595158
28	31.567638	0.595158
27	6.148263	0.595158
26	49.63817	0.595158
1	105.762117	0.595158
31	20.658877	0.595158
23	158.597896	0.595158
22	16.82718	0.595158

```
21      7.500133        0.595158
20    359.385191        0.595158
33        1000.0        0.595158
18     38.913655        0.595158
34    449.059292        0.595158
37    134.307189        0.595158
38    700.828495        0.595158
14     11.146207        0.595158
40      8.987967        0.595158
41    197.135766        0.595158
11    236.983664        0.595158
10    995.041655        0.595158
43     91.977108        0.595158
8     540.589888        0.595158
45        1000.0        0.595158
6       5.040529        0.595158
5      25.361101        0.595158
4      62.707668        0.595158
3       74.88174        0.595158
46     45.965476        0.595158
29    291.835129        0.595158
49      2.371127        0.594814
17      3.074934        0.594814
7       1.821455        0.594814
44       1.10021        0.594585
42      1.349826        0.594585
39      0.689484        0.594355
16      0.979426        0.594242
2       0.466654        0.592866
0       0.288818        0.591945
24      0.171718        0.589652
35      0.155587        0.589421
36        0.1141        0.586332
13      0.097524        0.586272
19      0.054925        0.578083
32      0.026621        0.565195
12      0.027451        0.565082
48      0.014315        0.544129
47      0.011414        0.532566
15      0.005206        0.503437
9       0.001051        0.500000
```

5.1.5 Scores for Logistic Regression with best parameters from Bayesian L1

[ ]:
```
best_model = bayes_search_1.best_estimator_
y_pred = best_model.predict(X_test)
print_scores(y_test, y_pred)
```

```
Accuracy = 0.8631, Balanced Accuracy = 0.5862
Precision = 0.5448, Recall = 0.2000, F1-score = 0.2926
Cost = 10355
```



The Bayesian-optimized Logistic Regression model with L1 regularization demonstrates an accuracy of 86.31% and a balanced accuracy of 58.62%. There is no improvement in the accuracy or balanced accuracy scores when the searching strategies are changed. The Bayesian optimization process likely contributed to fine-tuning hyperparameters for improved performance, but no improvment in the balanced accuracy was noticed.

5.1.6 Bayesian Optimization with L2

[ ]:
```
# Bayesian Optimization with L2
from skopt import BayesSearchCV

lrl2 = LogisticRegression(penalty='l2')

lr2_pipe = Pipeline([
    ('prep', prep_pipeline),
    ('model', lrl2)
])
```

```python
param_space = {
    'model__C': (0.001, 1000.0, 'log-uniform')
}

bayes_search_2 = BayesSearchCV(
    lr2_pipe,
    param_space,
    n_iter=50,
    cv=5,
    scoring='balanced_accuracy',
    random_state=42
)

bayes_search_2.fit(X_train, y_train)

cv_res = pd.DataFrame(bayes_search_2.cv_results_)
cv_res.sort_values(by="mean_test_score", ascending=False, inplace=True)
display(cv_res.filter(regex='(^param_|mean_test_score)', axis=1))
```

	param_model__C	mean_test_score
46	2.547234	0.595271
38	3.321972	0.595214
27	3.411386	0.595214
41	3.858294	0.595214
17	4.019829	0.595214
23	2.901769	0.595214
33	2.747669	0.595214
30	3.443508	0.595214
24	50.587	0.595158
1	105.762117	0.595158
26	395.813981	0.595158
29	227.438082	0.595158
28	137.207448	0.595158
21	16.629869	0.595158
31	206.863006	0.595158
34	31.559637	0.595158
35	337.243118	0.595158
40	9.331376	0.595158
37	20.604067	0.595158
22	761.975093	0.595158
25	7.616889	0.595158
20	38.973231	0.595158
39	703.265642	0.595158
3	74.88174	0.595158
4	62.707668	0.595158
5	25.361101	0.595158
6	5.040529	0.595158

```
8       540.589888          0.595158
45        6.205895          0.595158
11      999.841784          0.595158
43        13.69988          0.595158
13      289.822074          0.595158
14      999.416587          0.595158
15       11.287735          0.595158
19      178.489026          0.595158
7         1.821455          0.594985
44         1.10021          0.594754
32          1.1636          0.594754
16        1.189104          0.594754
49        0.719154          0.594237
2         0.466654          0.593435
0         0.288818          0.592970
36        0.182397          0.589651
12        0.099752          0.584674
42        0.046535          0.576883
10         0.03095          0.573097
48        0.014315          0.553114
47        0.011414          0.544011
18        0.006391          0.526502
9         0.001051          0.502402
```

5.1.7 Cost for Logistic Regression

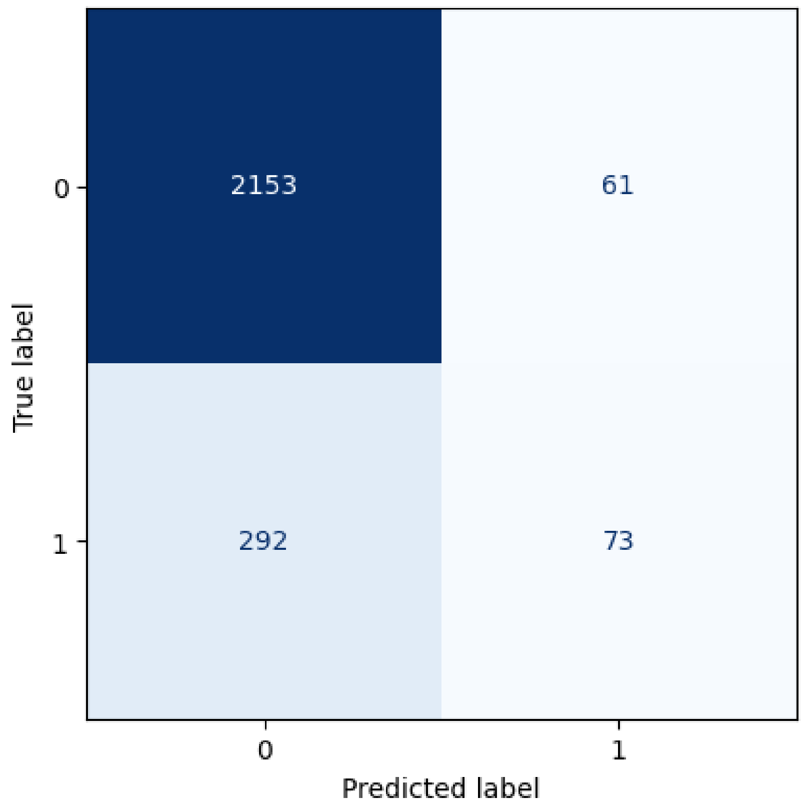
[ ]:
```
from sklearn.model_selection import cross_val_score
lr_costs = cross_val_score(lr_pipe, X_train, y_train, cv=5, scoring=cost_scorer)
print(f'The average cost of Logistic Regression is {lr_costs.mean():.1f}.')
```

```
The average cost of Logistic Regression is 8102.4.
```

5.1.8 Scores for Logistic Regression with best parameters from Bayesian L2

[ ]:
```
best_model = bayes_search_2.best_estimator_
y_pred = best_model.predict(X_test)
print_scores(y_test, y_pred)
```

```
Accuracy = 0.8631, Balanced Accuracy = 0.5862
Precision = 0.5448, Recall = 0.2000, F1-score = 0.2926
Cost = 10355
```

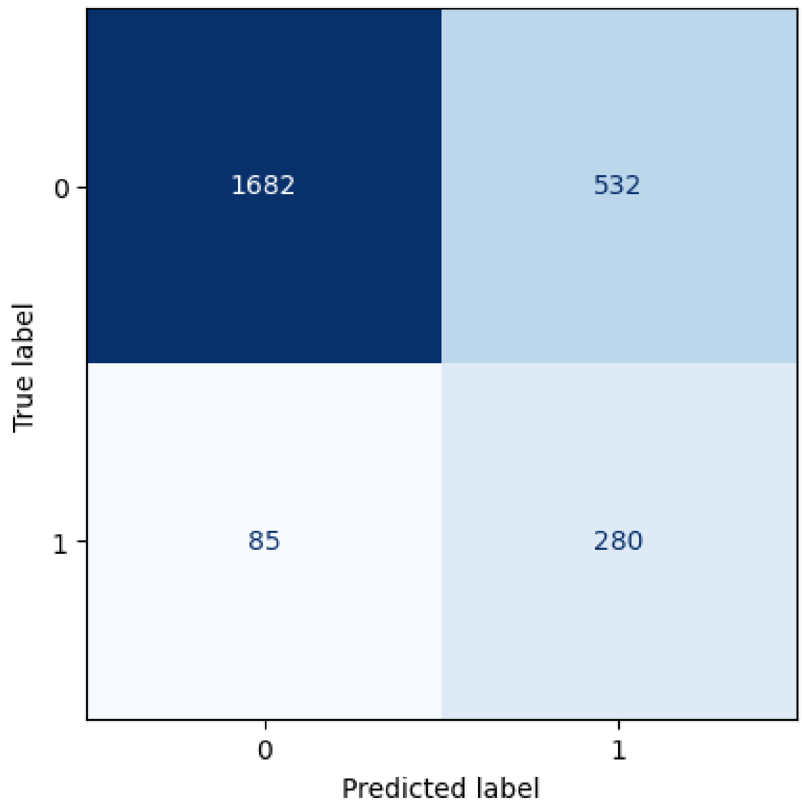


The Bayesian-optimized Logistic Regression model with L2 regularization exhibits an accuracy of 86.31% and a balanced accuracy of 58.62%. A different searching strategy did not yield improved results from that of grid search. Using L2 with Bayesian with L2 did not change results of the model.

5.1.9 Class Imbalance through SMOTENC - Logistic Regression

[ ]:
```
from imblearn.over_sampling import SMOTENC
from imblearn.pipeline import Pipeline, make_pipeline

lr_smote_pipe = make_pipeline(prep_pipeline,␣
 ↪SMOTENC(categorical_features=[6,7], random_state=42), LogisticRegression(C=2.
 ↪547234))
lr_smote_pipe.fit(X_train, y_train)
y_pred_smote = lr_smote_pipe.predict(X_test)
print_scores(y_test, y_pred_smote)
```

```
Accuracy = 0.7608, Balanced Accuracy = 0.7634
Precision = 0.3448, Recall = 0.7671, F1-score = 0.4758
Cost = 6614
```



5.2 2. K-Nearest Neighbors

5.2.1 KNN Pipeline

```
[ ]: from sklearn.model_selection import GridSearchCV
     from sklearn.neighbors import KNeighborsClassifier

     knn_pipeline = Pipeline([
         ('preprocessing', prep_pipeline),
         ('knn', KNeighborsClassifier()),
     ])

     knn_pipeline
```

```
[ ]: Pipeline(steps=[('preprocessing',
                      ColumnTransformer(transformers=[('num',
                                                       Pipeline(steps=[('imputer',
     SimpleImputer(strategy='median')),
                                                                       ('standard '
                                                                        'scaler',
     StandardScaler())]),
```

```
<sklearn.compose._column_transformer.make_column_selector object at
0x7d73a83a0640>),
                                                  ('cat',
                                                   Pipeline(steps=[('imputer',
SimpleImputer(strategy='most_frequent')),
('cat_encoder',
OneHotEncoder(drop='first'))]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7d73a790dbd0>)])),
                ('knn', KNeighborsClassifier())])
```

5.2.2 Grid Search

[ ]:

```
param_grid = [
    {'knn__n_neighbors': np.arange(2, 21, 2),
     'knn__p': np.arange(2, 21, 2)
     },
    ]

print('The parameter grid : ')
print(param_grid)

grid_search = GridSearchCV(knn_pipeline, param_grid, cv=3,
                                 scoring='balanced_accuracy',␣
 ↪error_score='raise')
grid_search.fit(X_train, y_train)
print('\n\nThe best parameters are ', grid_search.best_params_)

grid_cv_res = pd.DataFrame(grid_search.cv_results_)
grid_cv_res.sort_values(by='mean_test_score', ascending=False, inplace=True)
grid_cv_res.filter(regex = '(^param_|mean_test_score)', axis=1).head()
```

```
The parameter grid :
[{'knn__n_neighbors': array([ 2,  4,  6,  8, 10, 12, 14, 16, 18, 20]), 'knn__p':
array([ 2,  4,  6,  8, 10, 12, 14, 16, 18, 20])}]


The best parameters are  {'knn__n_neighbors': 2, 'knn__p': 2}
```

[ ]:

	param_knn__n_neighbors	param_knn__p	mean_test_score
0	2	2	0.830297
2	2	6	0.822074
5	2	12	0.821675
1	2	4	0.821562
7	2	16	0.820533

5.2.3 Random Search

[ ]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVC
from scipy.stats import randint

param_distribs = [
    {'knn__n_neighbors': randint(2, 20),
     'knn__p': randint(2, 20)
     },
    ]

random_search = RandomizedSearchCV(knn_pipeline, param_distribs, n_iter=25,␣
 ↪cv=3,
                                   scoring='balanced_accuracy', random_state=42)
random_search.fit(X_train, y_train)
random_search.best_estimator_
random_cv_res = pd.DataFrame(random_search.cv_results_)
random_cv_res.sort_values(by='mean_test_score', ascending=False, inplace=True)
random_cv_res.filter(regex = '(^param_|mean_test_score)', axis=1).head()
```

[ ]:

	param_knn__n_neighbors	param_knn__p	mean_test_score
5	3	13	0.835653
23	3	7	0.833930
7	2	13	0.820533
21	5	19	0.771951
6	7	3	0.761388

5.2.4 Scores and Costs

[ ]:
```
from sklearn.model_selection import cross_val_score

knn_scores = cross_val_score(knn_pipeline, X_train, y_train, cv=5,␣
 ↪scoring='balanced_accuracy')

print(f'The balanced accuracy of K Nearest Neighbor is {knn_scores.mean():.3f}.
 ↪')
```

```
The balanced accuracy of K Nearest Neighbor is 0.795.
```

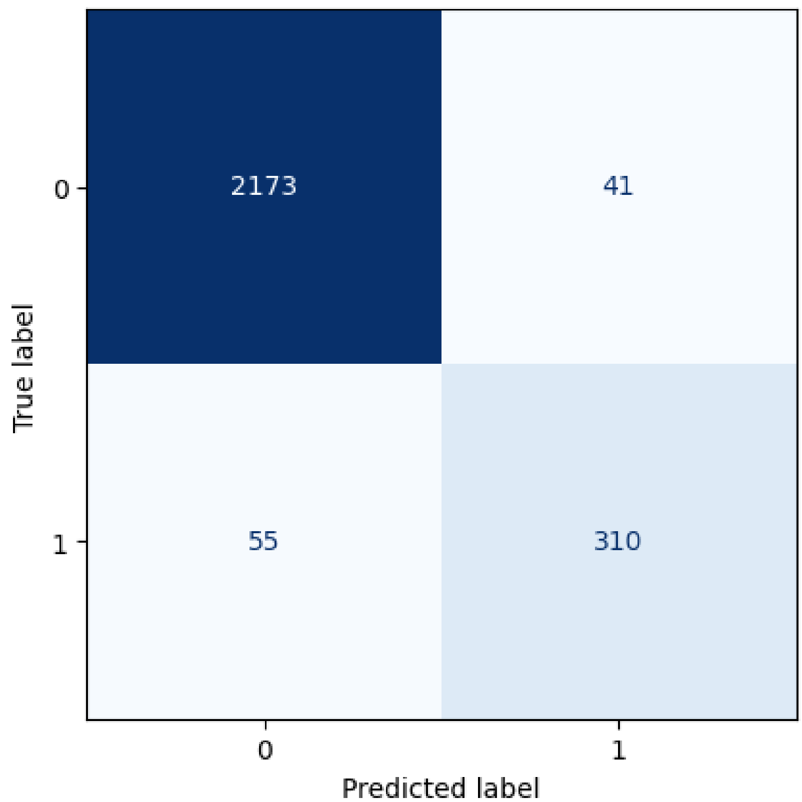
[ ]:
```
knn_costs = cross_val_score(knn_pipeline, X_train, y_train, cv=5,␣
 ↪scoring=cost_scorer)
print(f'The average cost of k-Nearest Neighbor is {knn_costs.mean():.1f}.')
```

```
The average cost of k-Nearest Neighbor is 4117.8.
```

5.2.5 Scores and Costs with Best Parameters

[ ]:
```
random_search.best_estimator_.fit(X_train,y_train)
y_pred = random_search.best_estimator_.predict(X_test)
print_scores(y_test, y_pred)
```

```
Accuracy = 0.9628, Balanced Accuracy = 0.9154
Precision = 0.8832, Recall = 0.8493, F1-score = 0.8659
Cost = 2157
```



After applying grid search and random search to find the best parameters, the K-Nearest Neighbors model using the result exhibits an accuracy of 96.28% and a balanced accuracy of 91.54%, which greatly improved the accuracy than before using the best parameters. The cost has also been reduced greatly from over 4000 dollars to 2157 dollars.

5.3 3. Decision Trees

5.3.1 Fit Dataset in Prep Pipeline

[ ]:
```
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.pipeline import make_pipeline
```

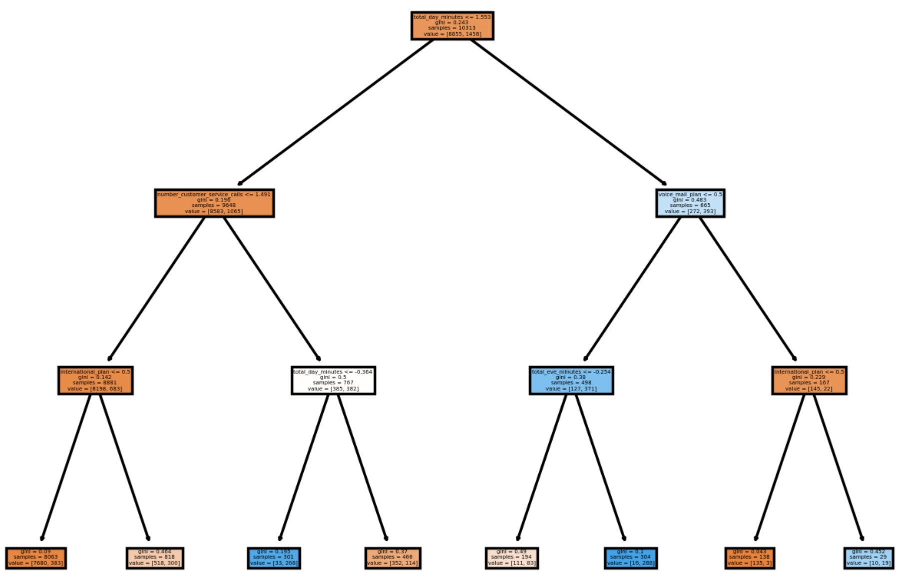
```
X_train_prepd = prep_pipeline.fit_transform(X_train)


X_test_prepd = prep_pipeline.transform(X_test)
```

Applying the preprocessing as a separate step and work with the transformed data

We are going to build a small tree, stopping after the depth has reached 3, just for our inspection. max_depth is only one of many arguments to limit the growth of a tree (control complexity, thus variance and overfitting, by incurring some bias). We use this because it most directly controls the look/structure of the tree (how tall we want it to be).

5.3.2 Create CLF Model and Fit it to the Train Data

[ ]:
```
clf = DecisionTreeClassifier(max_depth=3)

clf.fit(X_train_prepd, y_train)

plt.figure(dpi=250)
plot_tree(clf, filled=True, feature_names=list(X_train.columns));
```

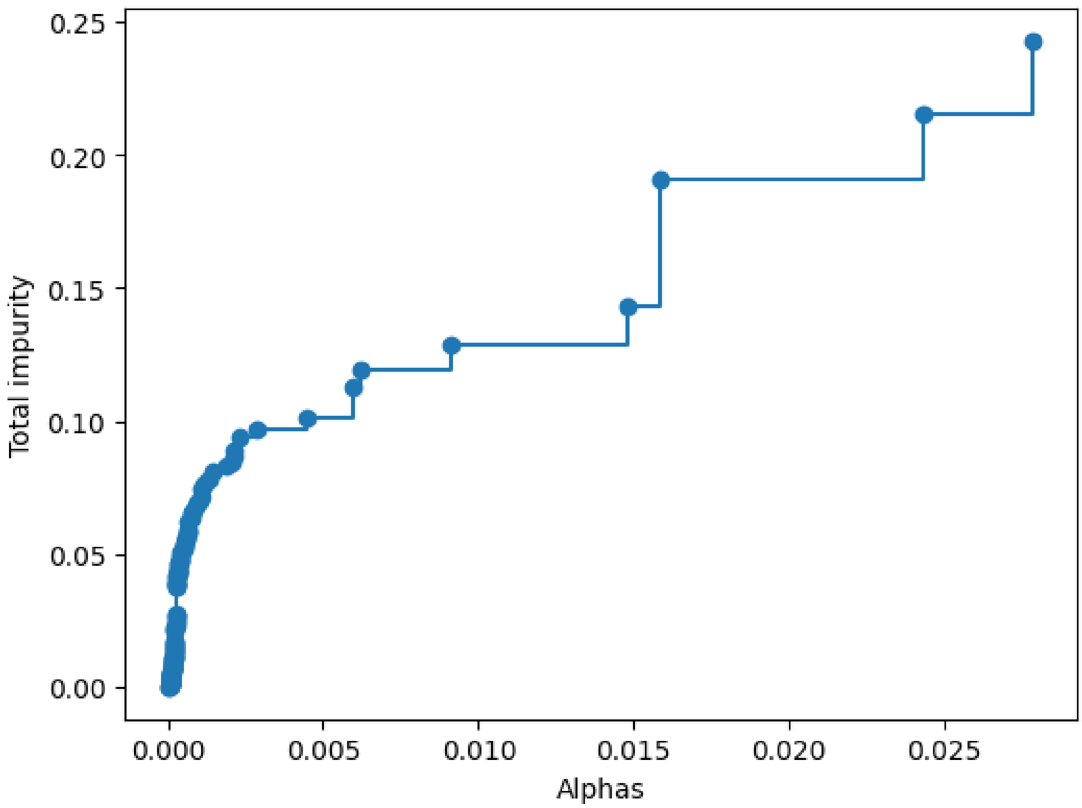


We have build a small tree, stopping after the depth has reached 3, just for our inspection. max_depth is only one of many arguments to limit the growth of a tree (control complexity, thus variance and overfitting, by incurring some bias). We use this because it most directly controls the look/structure of the tree (how tall we want it to be).

5.3.3 Visualizing the cost-complexity pruning path

[ ]:
```
clf_full = DecisionTreeClassifier()
path = clf_full.cost_complexity_pruning_path(X_train_prepd, y_train)
ccp_alphas, impurities = path.ccp_alphas, path.impurities # default impurity is␣
↪Gini
plt.plot(ccp_alphas, impurities, marker='o', drawstyle='steps-post')
plt.xlabel('Alphas'); plt.ylabel('Total impurity');

print(f'There are {ccp_alphas.shape[0]} alpha values.')
```

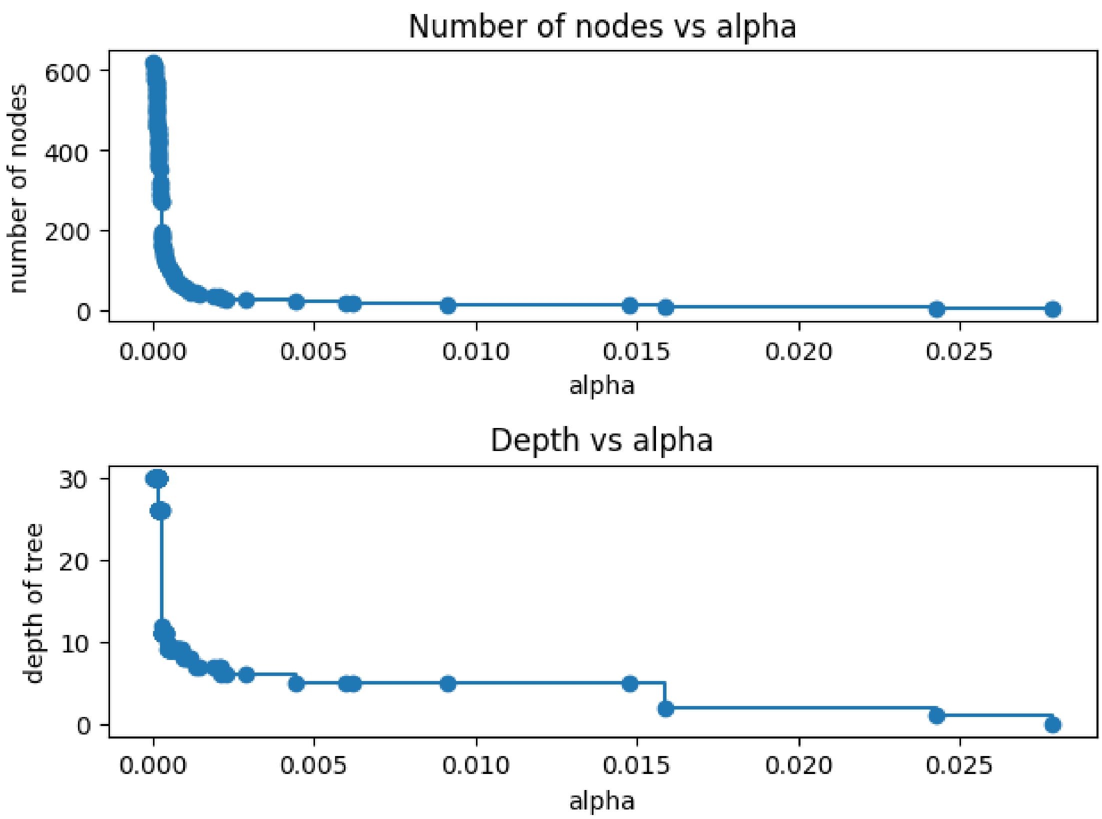
```
There are 133 alpha values.
```



At $\alpha = 0$ we have no pruning: the leaves will contain primarily one of the two classes, so low gini impurity index. At the largest α value, we have the gini of the original training data (without any split), therefore, high gini impurity index.

[ ]:
```
clfs = []
for ccp_alpha in ccp_alphas:
    clf_i = DecisionTreeClassifier(random_state=0, ccp_alpha=ccp_alpha)
```

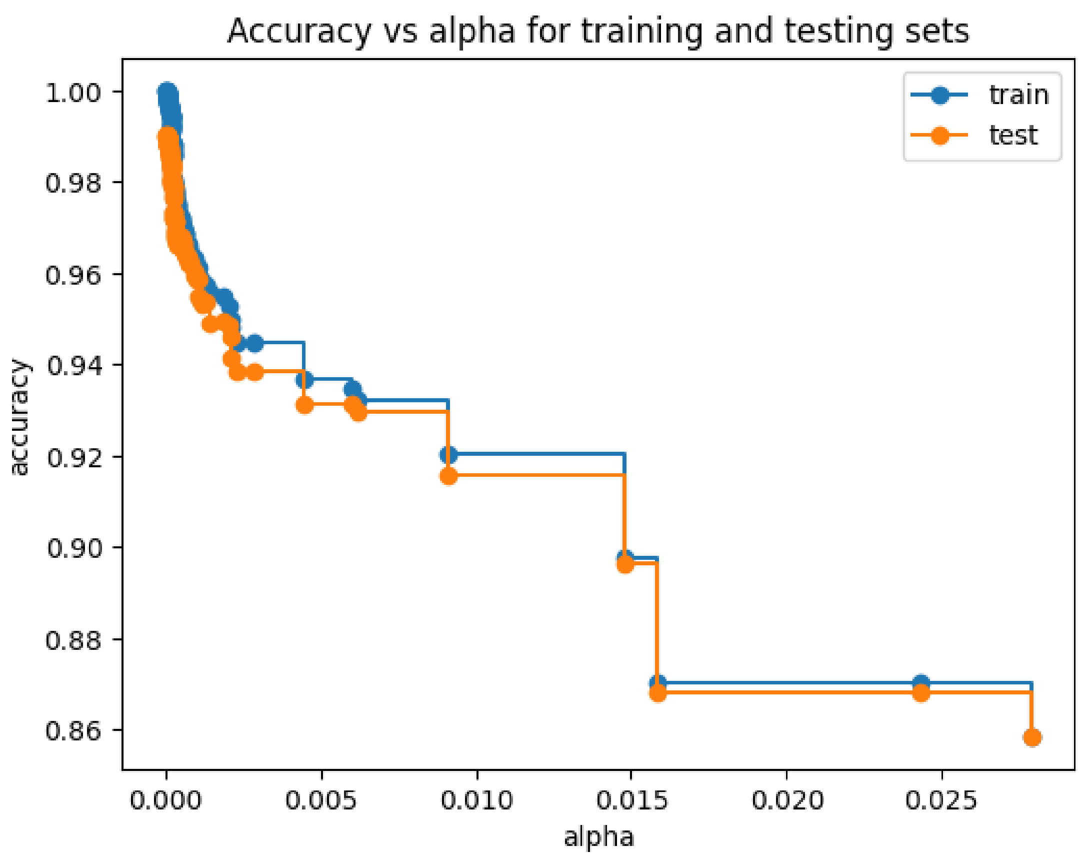
```
    clf_i.fit(X_train_prepd, y_train)
    clfs.append(clf_i)

node_counts = [clf_i.tree_.node_count for clf_i in clfs]
depth = [clf_i.tree_.max_depth for clf_i in clfs]

fig, ax = plt.subplots(2, 1, dpi=100)
ax[0].plot(ccp_alphas, node_counts, marker="o", drawstyle="steps-post")
ax[0].set_xlabel("alpha")
ax[0].set_ylabel("number of nodes")
ax[0].set_title("Number of nodes vs alpha")
ax[1].plot(ccp_alphas, depth, marker="o", drawstyle="steps-post")
ax[1].set_xlabel("alpha")
ax[1].set_ylabel("depth of tree")
ax[1].set_title("Depth vs alpha")
fig.tight_layout()
```



The trees get smaller as α increases. we wil see which one of those 133 trees predicts best.

5.3.4 Plotting Accuracy vs Alpha

[ ]:
```
train_scores = [clf_i.score(X_train_prepd, y_train) for clf_i in clfs]
test_scores = [clf_i.score(X_test_prepd, y_test) for clf_i in clfs]

fig, ax = plt.subplots(dpi=100)
ax.set_xlabel("alpha")
ax.set_ylabel("accuracy")
ax.set_title("Accuracy vs alpha for training and testing sets")
ax.plot(ccp_alphas, train_scores, marker="o", label="train",␣
 ↪drawstyle="steps-post")
ax.plot(ccp_alphas, test_scores, marker="o", label="test",␣
 ↪drawstyle="steps-post")
ax.legend()
plt.show()
```



The accuracy monotonically decreases with the α (as the tree gets smaller)

5.3.5 Grid Search for the optimal value of the (ccp_alpha)

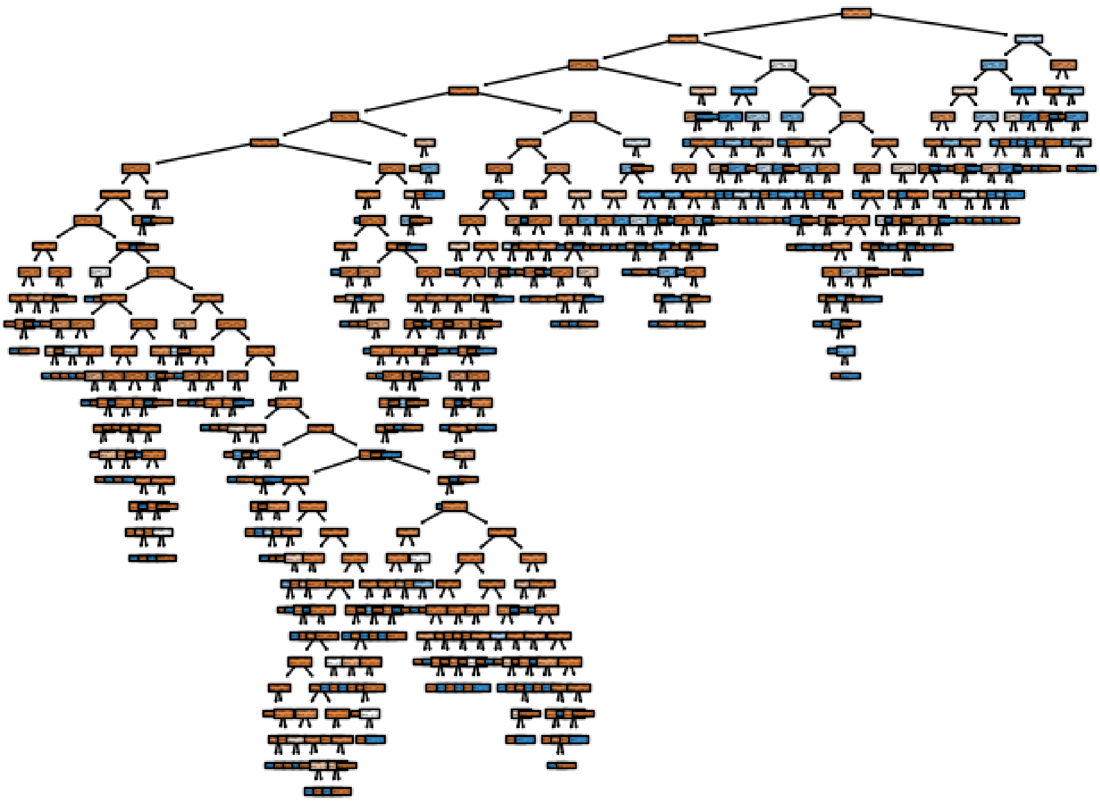
[ ]:
```
from sklearn.model_selection import GridSearchCV

param_grid = {'ccp_alpha': ccp_alphas}

grid_search = GridSearchCV(DecisionTreeClassifier(random_state=42), param_grid,␣
↪cv=5, scoring='accuracy')
grid_search.fit(X_train_prepd, y_train)

grid_cv_res = pd.DataFrame(grid_search.cv_results_)
grid_cv_res.sort_values(by="mean_test_score", ascending=False, inplace=True)
display(grid_cv_res.filter(regex = '(^param_|mean_test_score)', axis=1).head())
best_tree = grid_search.best_estimator_
print(f'The total number of nodes is {best_tree.tree_.node_count} and the max␣
↪depth is {best_tree.tree_.max_depth}.')
```

	param_ccp_alpha	mean_test_score
0	0.0	0.983515
1	0.000048	0.983515
2	0.000064	0.983419
3	0.000064	0.983419
4	0.000065	0.983419

```
The total number of nodes is 619 and the max depth is 30.
```

We have a relatively narrow range of alpha values with near best performances. Let's test the tree that corresponds to the best α:

[ ]:
```
fig, ax = plt.subplots()
plot_tree(best_tree, filled=True, feature_names=list(pd.
↪DataFrame(X_train_prepd).columns), impurity=False) # opt
fig.tight_layout()
```



5.3.6 Scores and Costs

[ ]:
```python
from sklearn.metrics import balanced_accuracy_score,accuracy_score



y_pred_clf = clf.predict(X_test_prepd)

print('Accuracy score :' ,accuracy_score(y_test,y_pred_clf))
print('Balanced accuracy score :' ,balanced_accuracy_score(y_test,y_pred_clf))
```

```
Accuracy score : 0.9026754556029469
Balanced accuracy score : 0.6836210416898689
```

[ ]:
```python
from sklearn.model_selection import cross_val_score
clf_costs = cross_val_score(clf, X_train, y_train, cv=5, scoring=cost_scorer)
print(f'The average cost of clf is {clf_costs.mean():.1f}.')
```

```
The average cost of clf is 6010.2.
```

[ ]:
```python
from sklearn.metrics import balanced_accuracy_score
best_model = grid_search.best_estimator_
```

```
y_pred_clf_best = best_model.predict(X_test_prepd) # predict on test data
test_balanced_accuracy = balanced_accuracy_score(y_test, y_pred_clf_best )  #␣
↪evaluate predictions
print(f'Balanced accuracy of the best found model on the test data is␣
↪{test_balanced_accuracy:.3f}')
print('Accuracy score of the best found model on the test data is:' ,␣
↪accuracy_score(y_test,y_pred_clf_best))
```

```
Balanced accuracy of the best found model on the test data is 0.979
Accuracy score of the best found model on the test data is: 0.9906940674680108
```

[ ]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_clf_best)
print(cm)
```

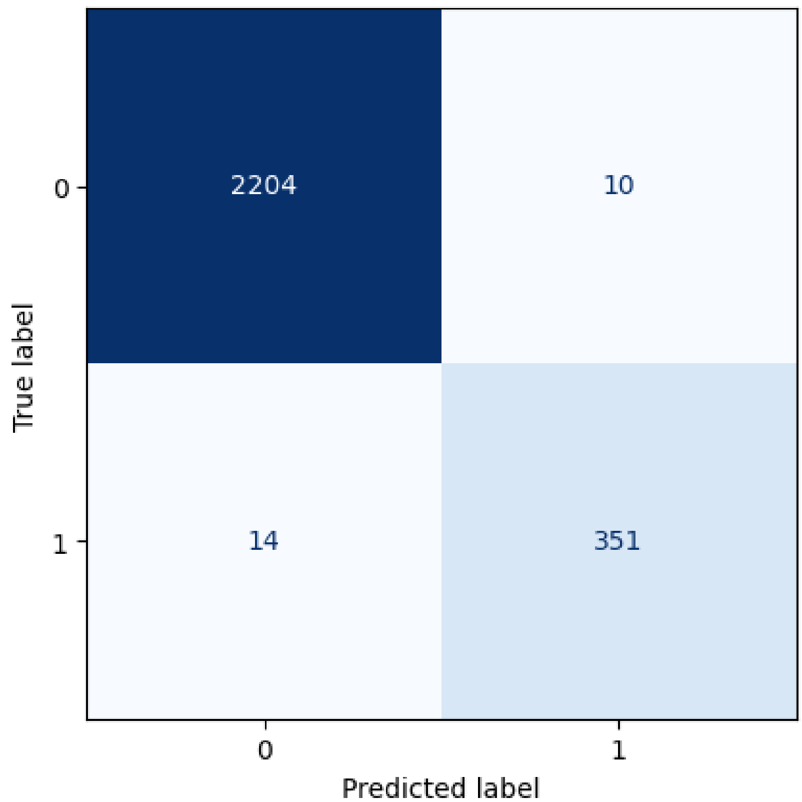
```
[[2204   10]
 [  14  351]]
```

[ ]:
```
# Calculate the cost on the test set
test_cost = default_cost(y_test, y_pred_clf_best)
print(f'The cost on the test set is {test_cost:.1f}.')
```

```
The cost on the test set is 546.0.
```

[ ]:
```
y_pred = best_model.predict(X_test_prepd)
print_scores(y_test, y_pred)
```

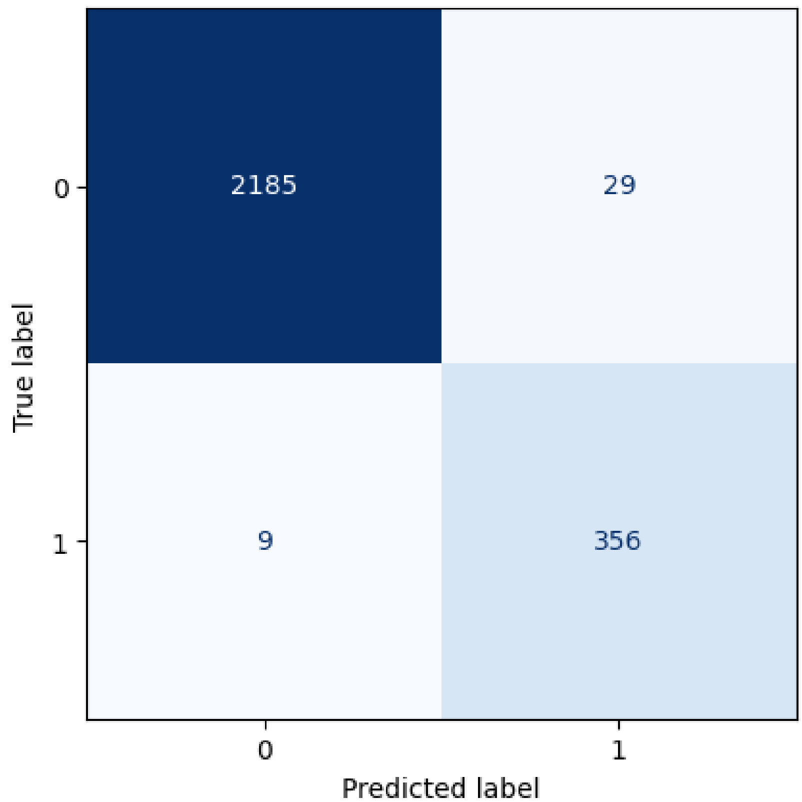
```
Accuracy = 0.9907, Balanced Accuracy = 0.9786
Precision = 0.9723, Recall = 0.9616, F1-score = 0.9669
Cost = 546
```



5.3.7 Class Imbalance through SMOTENC - Decision Tree

[ ]:
```
from imblearn.over_sampling import SMOTENC
from imblearn.pipeline import Pipeline, make_pipeline
from sklearn.tree import DecisionTreeClassifier

dt_smote_pipe = make_pipeline(prep_pipeline,␣
  ↪SMOTENC(categorical_features=[6,7], random_state=42),␣
  ↪DecisionTreeClassifier())
dt_smote_pipe.fit(X_train, y_train)
y_pred_smote = dt_smote_pipe.predict(X_test)
print_scores(y_test, y_pred_smote)
```

```
Accuracy = 0.9853, Balanced Accuracy = 0.9811
Precision = 0.9247, Recall = 0.9753, F1-score = 0.9493
Cost = 509
```



SMOTENC helped improve the model's performance, especially in capturing patterns within the minority class. In summary, the high balanced accuracy, precision, recall, and F1-score, along with a relatively low cost, suggest that the Decision Tree model, trained on a dataset with SMOTENC, effectively handles class imbalance.

5.4 4. SVM

After looking at the performance of the above models, we decided to try the Support Vector Machine to train and test the learning model. As we saw fromt he first model - Logistic Regression, the model does not perform like we do like for it to. It is safe to say that the model does not show a linear relationship. To test this theory, we use the SVM and tune it based on kernels (linear, poly or radial) as well as C and gamma for regularization.

Additionally, SVMs are less prone to overfitting and hence might prove to be a more reliable option (as we were considering a situation in which the decision tree model specified above could be overfitting).

5.4.1 Check support vectors and create Pipeline

[ ]:
```python
from sklearn.svm import SVC

lin_svc = SVC(kernel='linear')

svm_lin_pipeline = Pipeline([
    ("preprocessing", prep_pipeline),
    ("svm", lin_svc),
])

svm_lin_pipeline
```

[ ]:
```
Pipeline(steps=[('preprocessing',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='median')),
                                                                  ('standard '
                                                                   'scaler',
StandardScaler())]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7d73a83a0640>),
                                                 ('cat',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='most_frequent')),
('cat_encoder',
OneHotEncoder(drop='first'))]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7d73a790dbd0>)])),
                ('svm', SVC(C=2, kernel='linear'))])
```

[ ]:
```python
svm_lin_pipeline.fit(X_train, y_train)
y_pred_lin_svm = svm_lin_pipeline.predict(X_test)

print(lin_svc.n_support_)

cost_scorer(svm_lin_pipeline, X_test, y_test)
```

```
[1619 1458]
```

[ ]:
```
12410
```

5.4.2 Scores and Costs

[ ]:
```python
from sklearn.metrics import balanced_accuracy_score,accuracy_score

print('Accuracy score :' ,accuracy_score(y_test,y_pred_lin_svm))
```

```
print('Balanced accuracy score :'␣
↪,balanced_accuracy_score(y_test,y_pred_lin_svm))
```

```
Accuracy score : 0.8584722760759984
Balanced accuracy score : 0.5
```

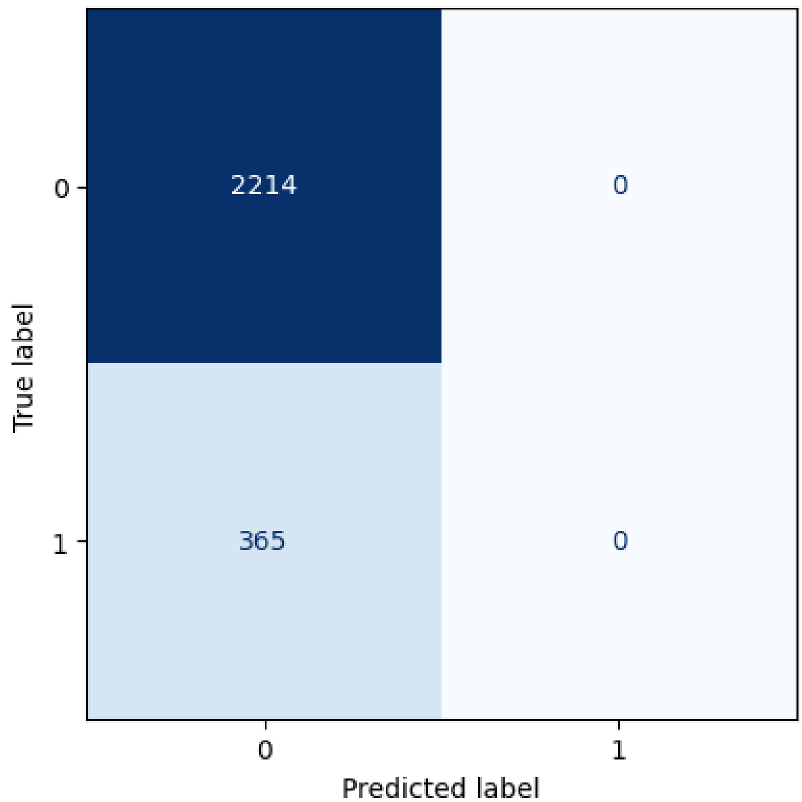
[ ]:
```
# Model Cost

from sklearn.model_selection import cross_val_score

svm_costs = cross_val_score(svm_lin_pipeline, X_train, y_train, cv=5,␣
↪scoring=cost_scorer)
print(f'The average cost of SVM is {svm_costs.mean():.1f}.')
```

```
The average cost of SVM is 9914.4.
```

[ ]:
```
print_scores(y_test,y_pred_lin_svm);
```

```
Accuracy = 0.8585, Balanced Accuracy = 0.5000
Precision = 0.0000, Recall = 0.0000, F1-score = 0.0000
Cost = 12410
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



Using linear Support Vector Machine (SVM) as a metric for model learning is suboptimal, as indicated by the balanced accuracy score of 0.5. This score suggests that the model's predictive performance is on par with random chance or a coin toss. A closer look at other performance metrics is not even needed as the imbalanced nature of the dataset renders them less informative than the balanced accuracy score.

To reap the benefits of a good SVM, we need to hyper tune the parameters. To achieve this, we experimented with various search strategies such as grid search, randomized search, and Bayesian search. However, these approaches proved computationally intensive and time-consuming due to the substantial number of parameters which requiring tuning. Consequently, we opted for the Halving Randomized Search strategy. It strikes a balance between efficiency and effectiveness, making it advantageous for tuning SVM parameters in such a large search space.

5.4.3 Halving Randomized Search

[ ]:
```
from sklearn.experimental import enable_halving_search_cv
from sklearn.svm import SVC
from sklearn.model_selection import HalvingRandomSearchCV
from scipy.stats import loguniform, randint

svm_hr_pipeline = Pipeline([
    ("preprocessing", prep_pipeline),
```

```
    ("svm", SVC()),
])

param_distr = [
  {'svm__kernel': ['linear'], 'svm__C': loguniform(1e-1, 1e+3)},
  {'svm__kernel': ['rbf'], 'svm__C': loguniform(1e-1, 1e+3), 'svm__gamma':␣
 ↪loguniform(1e-3, 1)},
  {'svm__kernel': ['poly'], 'svm__C': loguniform(1e-1, 1e+3), 'svm__gamma':␣
 ↪loguniform(1e-3, 1), 'svm__degree': randint(2, 5)},
]

random_search = HalvingRandomSearchCV(svm_hr_pipeline, param_distr, cv=3,
                                      n_candidates=40, min_resources='exhaust',
                                      scoring='balanced_accuracy',␣
 ↪random_state=0)
random_search.fit(X_train, y_train)

random_cv_res = pd.DataFrame(random_search.cv_results_)
random_cv_res.sort_values(by="mean_test_score", ascending=False, inplace=True)
random_cv_res.filter(regex = '(iter|^param_|mean_test_score|n_resources)',␣
 ↪axis=1)
```

[ ]:

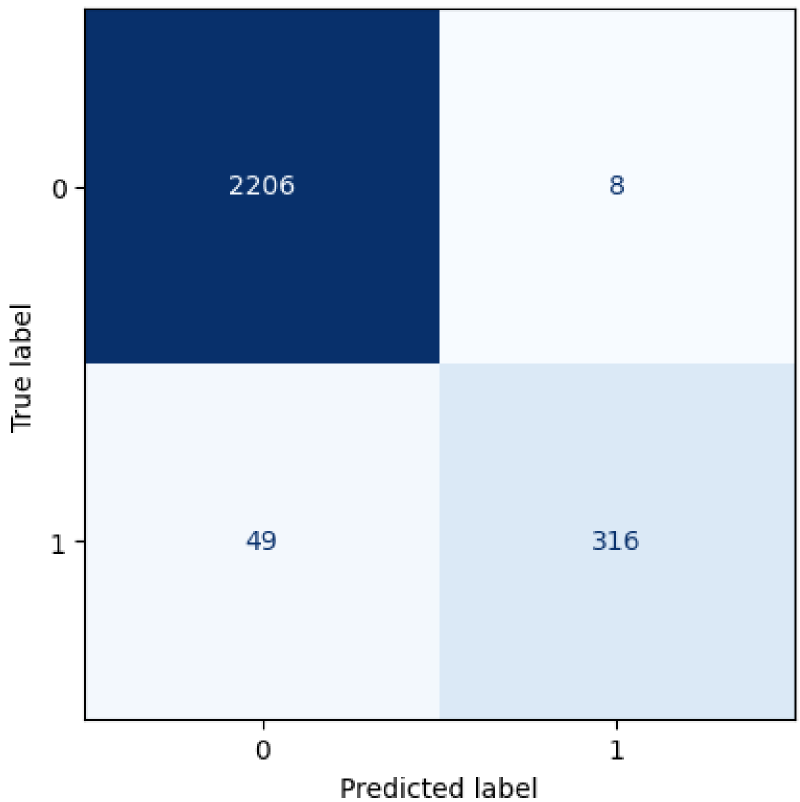
```
    iter  n_resources param_svm__C param_svm__kernel param_svm__gamma  \
60     3        10287    757.24475               rbf         0.091079
59     3        10287   325.667099               rbf         0.033797
55     2         3429    757.24475               rbf         0.091079
58     2         3429   325.667099               rbf         0.033797
57     2         3429    28.079081               rbf         0.070925
..   …          …          …                …              …
26     0          381     0.113315               rbf         0.073882
39     0          381     0.385272              poly         0.006457
35     0          381     1.880511              poly         0.002485
34     0          381     0.237554              poly         0.001776
30     0          381     0.120213               rbf         0.021141

   param_svm__degree  mean_test_score
60               NaN         0.914658
59               NaN         0.892165
55               NaN         0.874605
58               NaN         0.874338
57               NaN         0.867799
..               …            …
26               NaN         0.500000
39                 4         0.500000
35                 4         0.500000
34                 3         0.500000
30               NaN         0.500000
```

```
[61 rows x 7 columns]
```

5.4.4 Scores and Costs with Best Parameters

```
[ ]: y_pred = random_search.best_estimator_.predict(X_test)
     print_scores(y_test, y_pred)
```

```
Accuracy = 0.9779, Balanced Accuracy = 0.9311
Precision = 0.9753, Recall = 0.8658, F1-score = 0.9173
Cost = 1722
```



The hyper-tuned SVM model aligns with our initial assumption of a non-linear relationship within the dataset. The radial kernel with a coefficient of 0.091, and a regularisation strength of 757.24 helps us create a complex classification model with enhanced model accuracy, balanced accuracy, precision, recall, F1-score, and cost-effectiveness compared to the initial Linear SVM.

5.5 5. XGBoost - Ensemble Method

5.5.1 Preprocessing Data

[ ]:
```
tr_X = prep_pipeline.fit_transform(X_train)
tr_y = y_train

t_X = prep_pipeline.transform(X_test)
t_y = y_test

X_train.shape, tr_X.shape, tr_y.shape, t_X.shape, t_y.shape
```

[ ]:
```
((10313, 8), (10313, 8), (10313,), (2579, 8), (2579,))
```

5.5.2 Voting Classifier

[ ]:
```
from sklearn.ensemble import VotingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier

voting_clf = VotingClassifier(
    estimators=[
        ('dt', DecisionTreeClassifier(random_state=42)),
        ('svc', SVC(random_state=42)),
        ('knn', KNeighborsClassifier())

    ]
)

voting_clf.fit(tr_X, tr_y)
```

[ ]:
```
VotingClassifier(estimators=[('dt', DecisionTreeClassifier(random_state=42)),
                             ('svc', SVC(random_state=42)),
                             ('knn', KNeighborsClassifier())])
```

[ ]:
```
for name, clf in voting_clf.named_estimators_.items():
    print(f'Accuracy of {name} is {clf.score(t_X, t_y):.4f}')

print(f'Them voting give {voting_clf.score(t_X, t_y):.4f}')
```

```
Accuracy of dt is 0.9907
Accuracy of svc is 0.9624
Accuracy of knn is 0.9318
Them voting give 0.9767
```

```
[ ]: for name, clf in voting_clf.named_estimators_.items():
         balanced_acc = balanced_accuracy_score(t_y, clf.predict(t_X))
         print(f'Balanced Accuracy of {name} is {balanced_acc:.4f}')
     ensemble_balanced_acc = balanced_accuracy_score(t_y, voting_clf.predict(t_X))
     print(f'The voting ensemble has a Balanced Accuracy of {ensemble_balanced_acc:.
      ↪4f}')
```

```
Balanced Accuracy of dt is 0.9786
Balanced Accuracy of svc is 0.8797
Balanced Accuracy of knn is 0.8253
The voting ensemble has a Balanced Accuracy of 0.9201
```

The decision tree (dt) achieved a balance accuracy of 97.86%, the support vector machine (svc) achieved a balance accuracy of 87.97%, and the k-nearest neighbors (knn) achieved a balance accuracy of 82.53%. The ensemble method of voting, combining these models, resulted in an overall balanced accuracy of 92.01%. For svc and knn the voting classifier improve the model but for dt, it's already high, so we may try stacking to give more weight on dt which performs well.

5.5.3 Stacking Classifier

```
[ ]: from sklearn.ensemble import StackingClassifier, RandomForestClassifier

     stacking_clf = StackingClassifier(
         estimators=[
             ('dt', DecisionTreeClassifier(random_state=42)),
             ('svc', SVC(random_state=42)),
             ('knn', KNeighborsClassifier())
         ],
         final_estimator=XGBClassifier(random_state=42),
         cv=5
     )

     stacking_clf.fit(tr_X, tr_y)
```

```
[ ]: StackingClassifier(cv=5,
                        estimators=[('dt', DecisionTreeClassifier(random_state=42)),
                                    ('svc', SVC(random_state=42)),
                                    ('knn', KNeighborsClassifier())],
                        final_estimator=XGBClassifier(base_score=None, booster=None,
                                                      callbacks=None,
                                                      colsample_bylevel=None,
                                                      colsample_bynode=None,
                                                      colsample_bytree=None,
                                                      device=None,
                                                      early_stopping_rounds=None,
                                                      enable_categorical=False,
                                                      e…
                                                      grow_policy=None,
```

```
                                                    importance_type=None,
                                                    interaction_constraints=None,
                                                    learning_rate=None,
                                                    max_bin=None,
                                                    max_cat_threshold=None,
                                                    max_cat_to_onehot=None,
                                                    max_delta_step=None,
                                                    max_depth=None,
                                                    max_leaves=None,
                                                    min_child_weight=None,
                                                    missing=nan,
                                                    monotone_constraints=None,
                                                    multi_strategy=None,
                                                    n_estimators=None, n_jobs=None,
                                                    num_parallel_tree=None,
                                                    random_state=42, …))
```

5.5.4 Scores and Costs

[ ]:
```
print(f'Stacking the three has accuracy of {stacking_clf.score(t_X, t_y):.4f}')
from sklearn.metrics import balanced_accuracy_score, classification_report,␣
 ↪confusion_matrix, make_scorer
predictions = stacking_clf.predict(t_X)
print(f'Stacking the three has balance accuracy of␣
 ↪{balanced_accuracy_score(t_y, predictions):.4f}')
```

```
Stacking the three has accuracy of 0.9922
Stacking the three has balance accuracy of 0.9806
```

The stacking ensemble, which combines three models, achieved an accuracy of 99.22%. This suggests that the ensemble performed well in correctly predicting the class labels. The balance accuracy of the stacking ensemble is 98.06%. Balance accuracy takes into account the accuracy of each class, providing a more comprehensive evaluation, especially in imbalanced datasets.

[ ]:
```
report = classification_report(t_y, predictions)
print("Classification Report:\n", report)
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.99      1.00      1.00      2214
           1       0.98      0.96      0.97       365

    accuracy                           0.99      2579
   macro avg       0.99      0.98      0.98      2579
weighted avg       0.99      0.99      0.99      2579
```

[ ]:
```
confusion_matrix = confusion_matrix(t_y, predictions)
print(confusion_matrix)
```

```
[[2207    7]
 [  13  352]]
```

[ ]:
```
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix

def default_cost(y_true, y_pred):
    cm = confusion_matrix(y_true, y_pred)
    return cm[1, 0] * 34 + cm[0, 1] * 7

cost_scorer = make_scorer(default_cost)

xgb_costs = cross_val_score(stacking_clf, tr_X, tr_y, cv=5, scoring=cost_scorer)
print(f'The average cost of Stacking is {xgb_costs.mean():.1f}.')
```

```
The average cost of Stacking is 698.2.
```

The average cost of the stacking ensemble is 698.2. This cost metric reflects the combined impact of misclassifications and may involve different costs assigned to false positives and false negatives.

[ ]:
```
test_cost = default_cost(t_y, predictions)
print(f'The cost on the test set is {test_cost:.0f}.')
```

```
The cost on the test set is 491.
```

The cost on the test set for the stacking ensemble is 491. This indicates the total cost incurred by the model when making predictions on a separate set of data. A lower cost is generally desired, suggesting that the model is effective in minimizing misclassification costs.

In summary, the stacking ensemble demonstrated high accuracy and balance accuracy, while the cost metrics provide insights into the economic implications of the model's predictions. The lower cost on the test set suggests that the stacking ensemble performs well in terms of cost-effectiveness.

5.6 6. Random Forest

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score



rf_pipe = make_pipeline(prep_pipeline, RandomForestClassifier(n_estimators=100,␣
 ↪random_state=42))
rf_scores = cross_val_score(rf_pipe, X_train, y_train, cv=5,␣
 ↪scoring='balanced_accuracy')
rf_pipe.fit(X_train, y_train)

y_pred_rf= rf_pipe.predict(X_test)
```

```
print('Balanced accuracy score :' ,balanced_accuracy_score(y_test,y_pred_rf))
print(f'The balanced accuracy of Random Forest is {rf_scores.mean():.3f}.')
```

```
Balanced accuracy score : 0.9833358082439272
The balanced accuracy of Random Forest is 0.975.
```

[ ]:
```
from sklearn.model_selection import cross_val_score
clf_costs = cross_val_score(rf_pipe, X_train, y_train, cv=5,␣
 ↪scoring=cost_scorer)
print(f'The average cost of clf is {clf_costs.mean():.1f}.')
```

```
The average cost of clf is 499.6.
```

5.6.1 RandomizedSearchCV for Best Parameters

[ ]:
```
from sklearn.model_selection import RandomizedSearchCV

param_distribs = {
    'randomforestclassifier__max_depth': [int(x) for x in np.linspace(10, 100,␣
 ↪10)],
    'randomforestclassifier__min_samples_leaf': [1, 2, 4, 6, 8]
}

random_search = RandomizedSearchCV(rf_pipe, param_distribs, n_iter=20, cv=3,
                                   scoring='balanced_accuracy', random_state=42)

random_search.fit(X_train, y_train)

# Print the best estimator
print("Best Estimator:", random_search.best_estimator_)

# Display the best parameters and corresponding mean test score
random_rf_res = pd.DataFrame(random_search.cv_results_)
random_rf_res.sort_values(by='mean_test_score', ascending=False, inplace=True)
random_rf_res.filter(regex='(^param_|mean_test_score)', axis=1).head()
```

```
Best Estimator: Pipeline(steps=[('columntransformer',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='median')),
                                                                  ('standard '
                                                                   'scaler',
StandardScaler())]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7841da1b6ad0>),
                                                 ('cat',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='most_frequent')),
```

```
('cat_encoder',
OneHotEncoder(drop='first'))]),
<sklearn.compose._column_transformer.make_column_selector object at
0x7841da1b6a40>)])),
                ('randomforestclassifier',
                 RandomForestClassifier(max_depth=70, random_state=42))])
```

[ ]:
```
    param_randomforestclassifier__min_samples_leaf  \
19                                               1
2                                                1
3                                                1
7                                                1
17                                               2

    param_randomforestclassifier__max_depth  mean_test_score
19                                       40         0.962515
2                                        70         0.962515
3                                       100         0.962515
7                                        60         0.962515
17                                      100         0.936678
```

5.6.2 Scores and Cost

[ ]:
```python
from sklearn.metrics import balanced_accuracy_score,accuracy_score

best_model_rf = random_search.best_estimator_
y_pred_rf_best= best_model_rf.predict(X_test)
test_balanced_accuracy = balanced_accuracy_score(y_test, y_pred_rf_best)
print(f'Balanced accuracy of the best found model on the test data is␣
 ↪{test_balanced_accuracy:.2f}')
print('Accuracy score of the best found model on the test data is:' ,␣
 ↪accuracy_score(y_test,y_pred_rf_best))
```

```
Balanced accuracy of the best found model on the test data is 0.98
Accuracy score of the best found model on the test data is: 0.9949592865451725
```

[ ]:
```python
# Calculate the cost on the test set
test_cost = default_cost(y_test, y_pred_rf_best)
print(f'The cost on the test set is {test_cost:.1f}.')
```

```
The cost on the test set is 415.0.
```

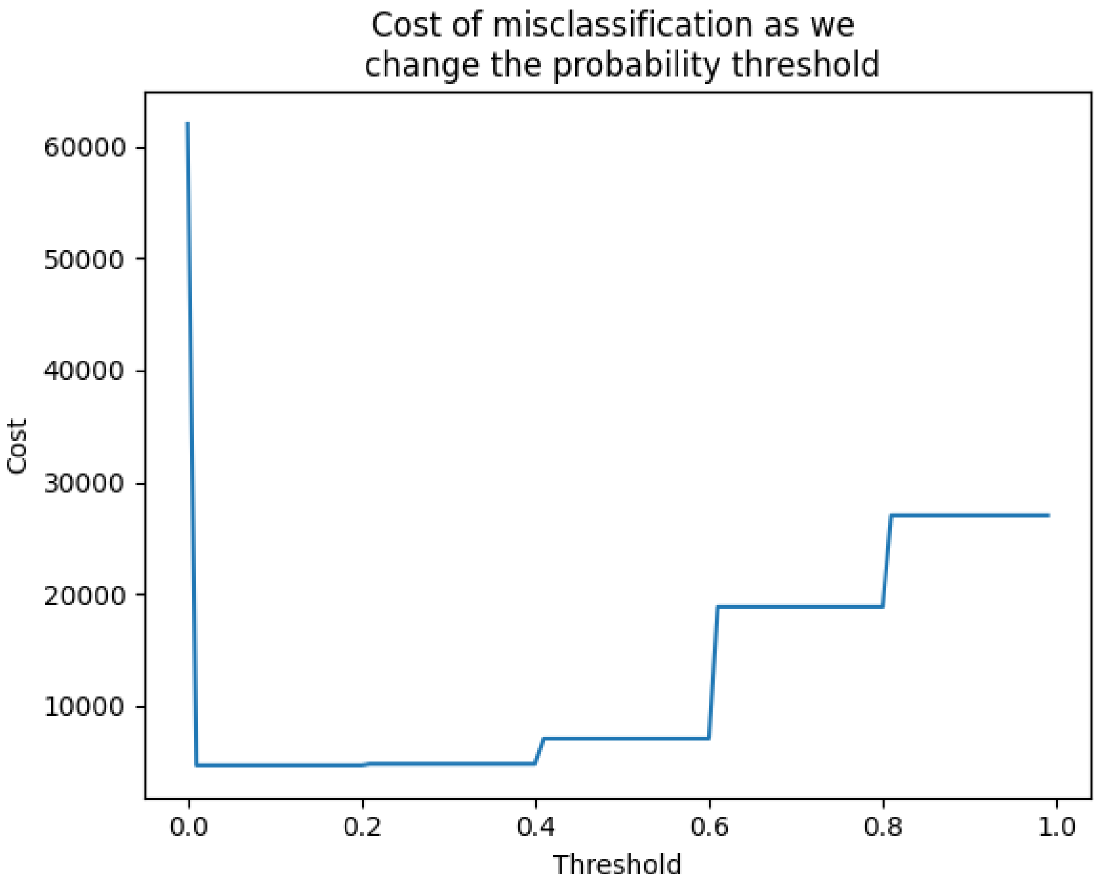
6 Cost Optimization

The aim of the the model is to now reduce the cost of misclasifications such that the model proves to be economical, on top of it being accurate. We try to find the optimal threshold whihc minimises the misclassification costs, such that every model probability greater than the threshold is classified as 1 (as misclassification of false negative is costlier).

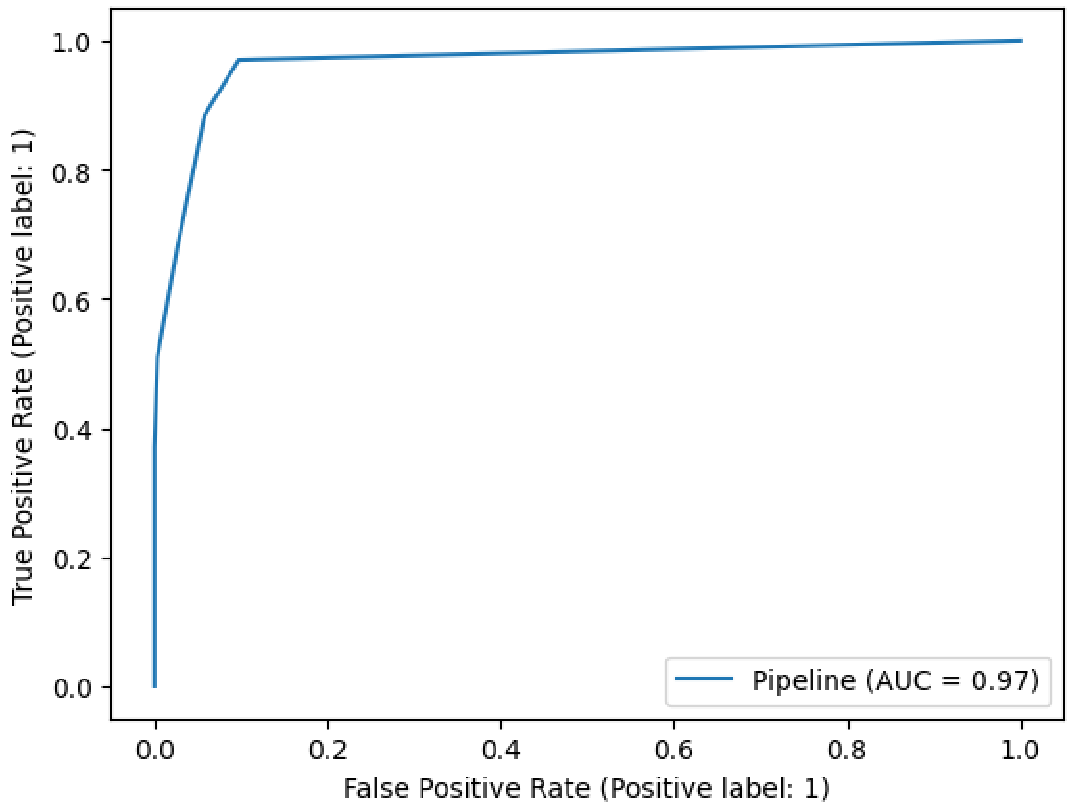
6.0.1 KNN

[ ]:
```
knn_pipeline.fit(X_train,y_train)

def predict_labels(pos_probs, threshold):
    return np.where(pos_probs >= threshold, 1, 0)

class_probabilities_knn = knn_pipeline.predict_proba(X_train)

probs_knn = class_probabilities_knn[:, 1]

step_size = 0.01
thresholds = np.arange(0, 1, step_size)

scores_knn = [default_cost(y_train, predict_labels(probs_knn, t)) for t in␣
 ↪thresholds]

ix = np.argmin(scores_knn)
opt_thresh_knn = thresholds[ix]

test_class_probabilities_knn = knn_pipeline.predict_proba(X_test)
test_probs_knn = test_class_probabilities_knn[:, 1]
opt_cost_knn = default_cost(y_test, predict_labels(test_probs_knn,␣
 ↪opt_thresh_knn))



print(f'After optimization, threshold should be set at {opt_thresh_knn:.2f},\
 which will lead to cost of misclassification of {opt_cost_knn}.')

plt.plot(thresholds, scores_knn);
plt.xlabel('Threshold'); plt.ylabel("Cost");
plt.title('Cost of misclassification as we \n change the probability␣
 ↪threshold');
```

```
After optimization, threshold should be set at 0.01, which will lead to cost of
misclassification of 1886.
```



[ ]:
```
from sklearn.metrics import RocCurveDisplay

RocCurveDisplay.from_estimator(knn_pipeline,X_test,y_test);
```

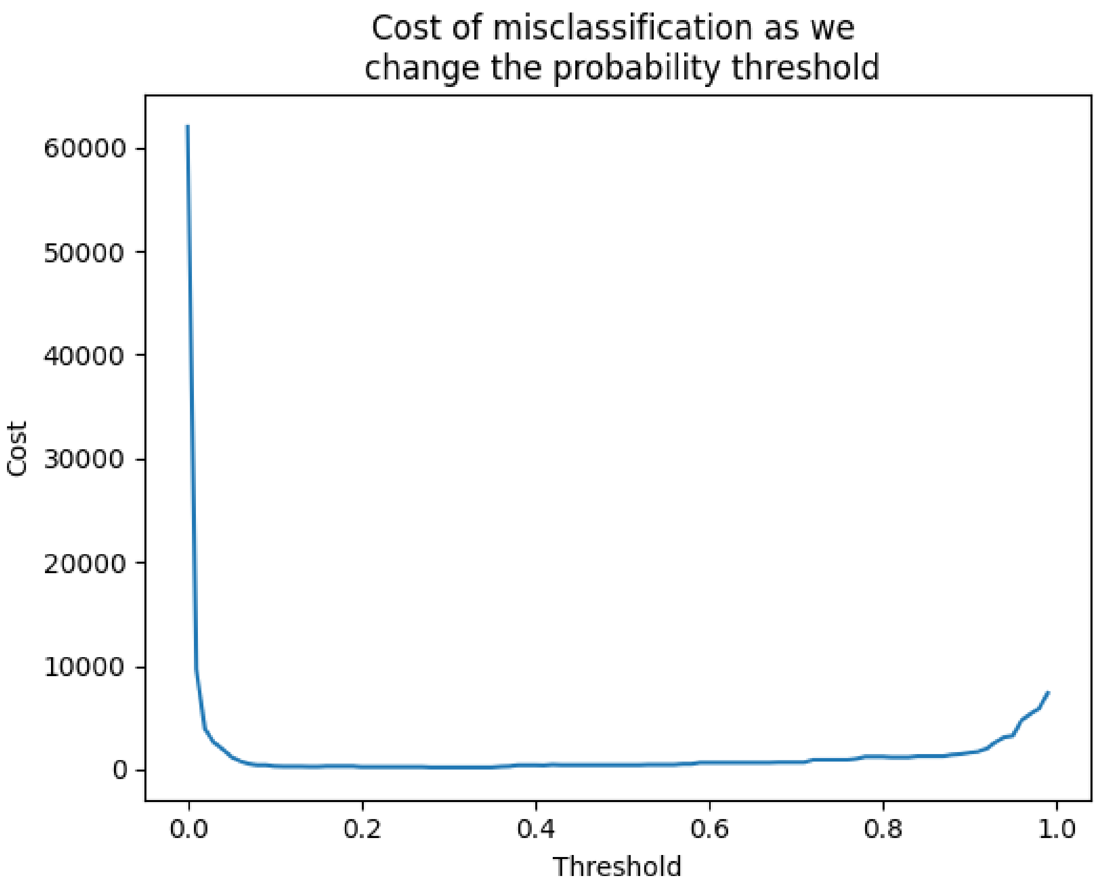


###Stacking

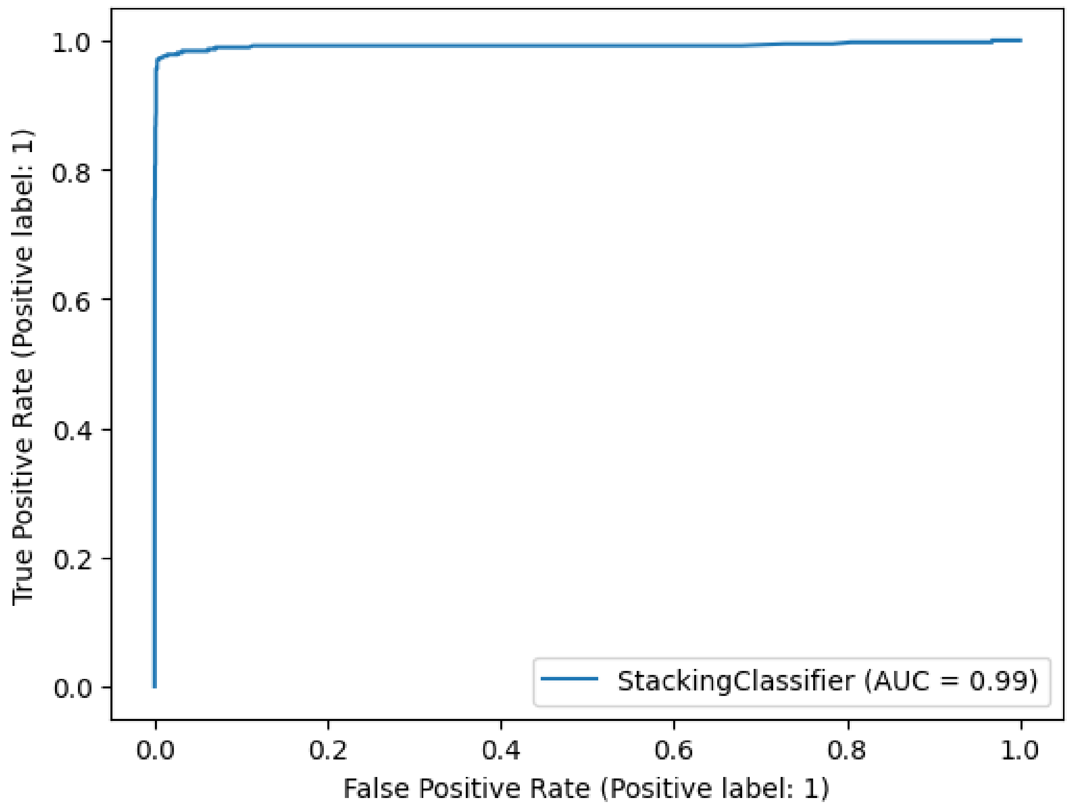
[ ]:
```
def predict_labels(pos_probs, threshold):
    return np.where(pos_probs >= threshold, 1, 0)

class_probabilities = stacking_clf.predict_proba(tr_X)

probs = class_probabilities[:, 1]

step_size = 0.01
thresholds = np.arange(0, 1, step_size)

scores = [default_cost(tr_y, predict_labels(probs, t)) for t in thresholds]

ix = np.argmin(scores)
opt_thresh = thresholds[ix]

test_class_probabilities = stacking_clf.predict_proba(t_X)
test_probs = test_class_probabilities[:, 1]
opt_cost = default_cost(t_y, predict_labels(test_probs, opt_thresh))
```

```
print(f'After optimization, threshold should be set at {opt_thresh:.2f},\
 which will lead to cost of misclassification of {opt_cost}.')


plt.plot(thresholds, scores);
plt.xlabel('Threshold'); plt.ylabel("Cost");
plt.title('Cost of misclassification as we \n change the probability␣
 ↪threshold');
```

```
After optimization, threshold should be set at 0.28, which will lead to cost of
misclassification of 444.
```



[ ]:
```
from sklearn.metrics import RocCurveDisplay

RocCurveDisplay.from_estimator(stacking_clf, t_X, t_y);
```



Tuning the threshold in the KNN model gives a probbaility threshold of 0.01, with a cost of USD 1886, and AUC as 0.97. Whereas, in the stacking cost optimization at the threshold of 0.28, cost is as low as USD 444 with 0.99 AUC.

7 Conclusion

In conclusion, the stacking method with XGBoost exhibits the best performance with a balanced accuracy of 0.9806 and an average cost reduction to $698.2 among 5 models applied. The ensemble method with stacking XGBoost is a model combining 3 best performance models which are decision tree, SVC and KNN.

8 Citations

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