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ChurnBackTime

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ChurnBackTime / Final.ipynb

falloutb1tch final push 11 minutes ago

6584 lines (6584 loc) · 353 KB

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If I Could Churn Back Time

... we wouldn't need these models, gnome sayin'?

Overview

For my capstone project, I have chosen to continue in a similar vein to my Phase 3 project with entirely different data. Churn, which is what it is called when a customer stops doing business with a company, is one of the largest issues facing almost every industry today. In context of subscription industries, for example, "churn" is a massive ongoing issue, as it is infinitely cheaper to keep existing customers than to lure in new ones. Therefore, establishing a procedure to keep customers from "churning" is of the utmost importance. The first step in this process is identifying the reasons behind customer churn, such as dissatisfaction, area of service provided, quality of service, and other such considerations. Following that, we will build a model that will accurately predict whether or not a customer will churn, and thereby provide the limitlessly valuable opportunity for a company to prevent that churn.

Business Understanding

As previously stated, it is much cheaper to keep existing customers than to continually lure new customers in. In other words, the longer a customer stays with a company, the more money that company stands to make from them. It seems fairly simple in that context, right? So it also follows that if there was a way to accurately predict whether or not a customer would churn, that method would be likely to save a company a boatload of money. And no, "boatload" in this case is not an exaggeration - the data we are using today comes from a fictional telecommunications company, but the very real company known as Verizon walked away from 2023 with $134 billion in total operating revenue. So our goal here was quite simple - build a model that could accurately predict when a customer would stop doing business with a company, and provide that company an opportunity to stop that customer from churning, thereby saving them money.

Data Understanding & Preparation

The data we've used for this endeavor comes to us from IBM, and is a publicly available dataset created for this exact purpose - to help deal with churn problems, and allow students like me to cut our teeth on such before we enter the wider world of data science. This sample data module tracks a fictional Telco company's customer churn based on a variety of possible factors, such as gender, monthly charges, and usage information, as well as whether the customer churned or not. Due to the nature of the data we used, any location based features were excluded because the data was all centered in California specifically.

In [1]:
```
import pandas as pd
```

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score, Randomi
from sklearn.pipeline import Pipeline as ImbPipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.dummy import DummyClassifier
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.metrics import classification_report, ConfusionMatrixDisplay, Roc
from sklearn.metrics import make_scorer
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_
from sklearn import tree
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
```

Our first step in data understanding is to load in our various Excel spreadsheets and transform them into Pandas dataframes to be explored. Our first exploratory steps will inform the rest of the process from cleaning the data to modeling, all the way to our final recommendations.

In [2]:

```
churn_df = pd.read_excel('Data/CustomerChurn.xlsx')
```

In [3]:

```
churn_df
```

Out[3]:

	LoyaltyID	Customer ID	Senior Citizen	Partner	Dependents	Tenure	Phone Service	Multiple Lines
0	318537	7590-VHVEG	No	Yes	No	1	No	No phone service
1	152148	5575-GNVDE	No	No	No	34	Yes	No
2	326527	3668-QPYBK	No	No	No	2	Yes	No
3	845894	7795-CFOCW	No	No	No	45	No	No phone service
4	503388	9237-HQITU	No	No	No	2	Yes	No
...	...	...	...	...	...	...	...	...
7038	810338	6840-RESVB	No	Yes	Yes	24	Yes	Yes
7039	230811	2234-XADUH	No	Yes	Yes	72	Yes	Yes
7040	155157	4801-JZAZL	No	Yes	Yes	11	No	No phone service

7041	731782	8361-LTMKD	Yes	Yes	No	4	Yes	Yes
7042	353947	3186-AJIEK	No	No	No	66	Yes	No

7043 rows × 21 columns

In [4]:

```
churn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   LoyaltyID          7043 non-null   int64  
 1   Customer ID        7043 non-null   object 
 2   Senior Citizen     7043 non-null   object 
 3   Partner            7043 non-null   object 
 4   Dependents         7043 non-null   object 
 5   Tenure             7043 non-null   int64  
 6   Phone Service      7043 non-null   object 
 7   Multiple Lines     7043 non-null   object 
 8   Internet Service   7043 non-null   object 
 9   Online Security    7043 non-null   object 
 10  Online Backup      7043 non-null   object 
 11  Device Protection  7043 non-null   object 
 12  Tech Support       7043 non-null   object 
 13  Streaming TV       7043 non-null   object 
 14  Streaming Movies   7043 non-null   object 
 15  Contract           7043 non-null   object 
 16  Paperless Billing  7043 non-null   object 
 17  Payment Method     7043 non-null   object 
 18  Monthly Charges    7043 non-null   float64
 19  Total Charges      7043 non-null   object 
 20  Churn              7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

In [5]:

```
churn_df.isna().sum()
```

Out[5]:

```
LoyaltyID            0
Customer ID          0
Senior Citizen       0
Partner              0
Dependents           0
Tenure               0
Phone Service        0
Multiple Lines       0
Internet Service     0
Online Security      0
Online Backup        0
Device Protection    0
Tech Support         0
Streaming TV         0
Streaming Movies     0
Contract             0
Paperless Billing    0
Payment Method       0
Monthly Charges      0
Total Charges        0
Churn                0
```

```
dtype: int64
```

Right off the bat with our first dataframe, we can see that there are no null values and that our dataframe contains floats and ints (which are numbers) and objects. Something to note is that "Total Charges" is listed as an object and it likely ought to be an int or a float. After some fiddling, it became clear that this was going to be troublesome, but I found myself in luck - our third dataset has properly formatted information about charges for various services as well as total charges overall, so we will not need to keep that information in this dataset at all.

In [6]:
```
churn_df = churn_df.drop(['LoyaltyID', 'Total Charges', 'Monthly Charges'], ax
```

In [7]:
```
churn_df
```

Out[7]:

	Customer ID	Senior Citizen	Partner	Dependents	Tenure	Phone Service	Multiple Lines	Internet Service	S
0	7590-VHVEG	No	Yes	No	1	No	No phone service	DSL	
1	5575-GNVDE	No	No	No	34	Yes	No	DSL	
2	3668-QPYBK	No	No	No	2	Yes	No	DSL	
3	7795-CFOCW	No	No	No	45	No	No phone service	DSL	
4	9237-HQITU	No	No	No	2	Yes	No	Fiber optic	
...	...	...	...	...	...	...	...	...	
7038	6840-RESVB	No	Yes	Yes	24	Yes	Yes	DSL	
7039	2234-XADUH	No	Yes	Yes	72	Yes	Yes	Fiber optic	
7040	4801-JZAZL	No	Yes	Yes	11	No	No phone service	DSL	
7041	8361-LTMKD	Yes	Yes	No	4	Yes	Yes	Fiber optic	
7042	3186-AJIEK	No	No	No	66	Yes	No	Fiber optic	

7043 rows × 18 columns

Now, we will repeat these same steps with the other relevant datasets.

In [8]:

```
telco_churn = pd.read_excel('Data/Telco_customer_churn.xlsx')
```

In [9]:

```
telco_churn
```

Out[9]:

	CustomerID	Count	Country	State	City	Zip Code	Lat Long	Latitude
0	3668-QPYBK	1	United States	California	Los Angeles	90003	33.964131, -118.272783	33.964131
1	9237-HQITU	1	United States	California	Los Angeles	90005	34.059281, -118.30742	34.059281
2	9305-CDSKC	1	United States	California	Los Angeles	90006	34.048013, -118.293953	34.048013
3	7892-POOKP	1	United States	California	Los Angeles	90010	34.062125, -118.315709	34.062125
4	0280-XJGEX	1	United States	California	Los Angeles	90015	34.039224, -118.266293	34.039224
...	...	...	...	...	...	...	...	..
7038	2569-WGERO	1	United States	California	Landers	92285	34.341737, -116.539416	34.341737
7039	6840-RESVB	1	United States	California	Adelanto	92301	34.667815, -117.536183	34.667815
7040	2234-XADUH	1	United States	California	Amboy	92304	34.559882, -115.637164	34.559882
7041	4801-JZAZL	1	United States	California	Angelus Oaks	92305	34.1678, -116.86433	34.167800
7042	3186-AJIEK	1	United States	California	Apple Valley	92308	34.424926, -117.184503	34.424926

7043 rows × 33 columns

In [10]:

```
telco_churn.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 33 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   CustomerID         7043 non-null   object
 1   Count              7043 non-null   int64
 2   Country            7043 non-null   object
 3   State              7043 non-null   object
 4   City               7043 non-null   object
 5   Zip Code           7043 non-null   int64
```

```
 6   Lat Long           7043 non-null   object
 7   Latitude           7043 non-null   float64
 8   Longitude          7043 non-null   float64
 9   Gender             7043 non-null   object
 10  Senior Citizen     7043 non-null   object
 11  Partner            7043 non-null   object
 12  Dependents         7043 non-null   object
 13  Tenure Months      7043 non-null   int64
 14  Phone Service      7043 non-null   object
 15  Multiple Lines     7043 non-null   object
 16  Internet Service   7043 non-null   object
 17  Online Security    7043 non-null   object
 18  Online Backup      7043 non-null   object
 19  Device Protection  7043 non-null   object
 20  Tech Support       7043 non-null   object
 21  Streaming TV       7043 non-null   object
 22  Streaming Movies   7043 non-null   object
 23  Contract           7043 non-null   object
 24  Paperless Billing  7043 non-null   object
 25  Payment Method     7043 non-null   object
 26  Monthly Charges    7043 non-null   float64
 27  Total Charges      7043 non-null   object
 28  Churn Label        7043 non-null   object
 29  Churn Value        7043 non-null   int64
 30  Churn Score        7043 non-null   int64
 31  CLTV               7043 non-null   int64
 32  Churn Reason       1869 non-null   object
dtypes: float64(3), int64(6), object(24)
memory usage: 1.8+ MB
```

There are a few immediate issues with this dataframe. Firstly, while "Churn Reason" seems like it might be very useful for modeling purposes, the column is also full of nulls, and so must be removed. Any location information can be removed because this dataset is based entirely in California, so any location-based reasonings would not be sound. We must also compare this dataframe to the first one and remove any duplicate or unnecessary columns, for ease of merging the two dataframes into one useful one. Many of these columns also "overlap" with our first dataframe, and therefore are unnecessary.

In [11]:

```
telco_churn = telco_churn.drop(['Count', 'Country', 'State', 'City', 'Zip Code
```

In [12]:

```
telco_churn
```

Out[12]:

	CustomerID	Gender	Churn Value	Churn Score	CLTV
0	3668-QPYBK	Male	1	86	3239
1	9237-HQITU	Female	1	67	2701
2	9305-CDSKC	Female	1	86	5372
3	7892-POOKP	Female	1	84	5003
4	0280-XJGEX	Male	1	89	5340
...	...	...	...	...	...
7038	2569-WGERO	Female	0	45	5306
7039	6840-RESVB	Male	0	59	2140
7040	2234-XADUH	Female	0	71	5560

7041	4801-JZAZL	Female	0	59	2793
7042	3186-AJIEK	Male	0	38	5097

7043 rows × 5 columns

In [13]:
```
telco_churn = telco_churn.rename(columns={'CustomerID': 'Customer ID'})
```

In [14]:
```
telco_churn
```

Out[14]:

	Customer ID	Gender	Churn Value	Churn Score	CLTV
0	3668-QPYBK	Male	1	86	3239
1	9237-HQITU	Female	1	67	2701
2	9305-CDSKC	Female	1	86	5372
3	7892-POOKP	Female	1	84	5003
4	0280-XJGEX	Male	1	89	5340
...	...	...	...	...	...
7038	2569-WGERO	Female	0	45	5306
7039	6840-RESVB	Male	0	59	2140
7040	2234-XADUH	Female	0	71	5560
7041	4801-JZAZL	Female	0	59	2793
7042	3186-AJIEK	Male	0	38	5097

7043 rows × 5 columns

In [15]:
```
telco_churn.isna().sum()
```

Out[15]:
```
Customer ID    0
Gender         0
Churn Value    0
Churn Score    0
CLTV           0
dtype: int64
```

Now, both of these dataframes are ready to be merged together, using Customer ID as a joining point since they are shared between them. This will add a few more features to our eventual modeling process, and I am specifically interested in gender as a feature here simply because it will be fascinating to see whether gender has any bearing on whether or not a customer stopped doing business with a company. I doubt it, but it is a unique viewpoint to consider.

We do have one final dataset that contains a few more services that could be used as features for modeling to determine whether those services (or lack thereof) have any impact on whether a customer will churn or not, so now, we will go through the same process one last time to assemble a third cleaned dataframe for our modeling purposes.

In [16]:

```
services_df = pd.read_excel('Data/Telco_customer_churn_services.xlsx')
```

In [17]:

```
services_df
```

Out[17]:

	Service ID	Customer ID	Count	Quarter	Referred a Friend	Number of Referrals	Tenure in Months	Offe
0	IJKDQVSWH3522	8779-QRDMV	1	Q3	No	0	1	None
1	BFKMZJAIE2285	7495-OOKFY	1	Q3	Yes	1	8	Offe I
2	EIMVJQBMT7187	1658-BYGOY	1	Q3	No	0	18	Offe D
3	EROZQXDUU4979	4598-XLKNJ	1	Q3	Yes	1	25	Offe C
4	GEEYSJUHY6991	4846-WHAFZ	1	Q3	Yes	1	37	Offe C
...	...	...	...	...	...	...	...	..
7038	JIVEOZUQQ2296	2569-WGERO	1	Q3	No	0	72	None
7039	OIQWIUTDY3518	6840-RESVB	1	Q3	Yes	1	24	Offe C
7040	QSHQPZAYF6519	2234-XADUH	1	Q3	Yes	4	72	None
7041	PMJLYZGVQ7211	4801-JZAZL	1	Q3	Yes	1	11	None
7042	BILLTTPVG8428	3186-AJIEK	1	Q3	No	0	66	None

7043 rows × 31 columns

In [18]:

```
services_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 31 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   Service ID                         7043 non-null   object
 1   Customer ID                        7043 non-null   object
 2   Count                              7043 non-null   int64
 3   Quarter                            7043 non-null   object
 4   Referred a Friend                  7043 non-null   object
 5   Number of Referrals                7043 non-null   int64
```

```
 6   Tenure in Months                    7043 non-null   int64
 7   Offer                               7043 non-null   object
 8   Phone Service                       7043 non-null   object
 9   Avg Monthly Long Distance Charges   7043 non-null   float64
 10  Multiple Lines                      7043 non-null   object
 11  Internet Service                    7043 non-null   object
 12  Internet Type                       7043 non-null   object
 13  Avg Monthly GB Download             7043 non-null   int64
 14  Online Security                     7043 non-null   object
 15  Online Backup                       7043 non-null   object
 16  Device Protection Plan              7043 non-null   object
 17  Premium Tech Support                7043 non-null   object
 18  Streaming TV                        7043 non-null   object
 19  Streaming Movies                    7043 non-null   object
 20  Streaming Music                     7043 non-null   object
 21  Unlimited Data                      7043 non-null   object
 22  Contract                            7043 non-null   object
 23  Paperless Billing                   7043 non-null   object
 24  Payment Method                      7043 non-null   object
 25  Monthly Charge                      7043 non-null   float64
 26  Total Charges                       7043 non-null   float64
 27  Total Refunds                       7043 non-null   float64
 28  Total Extra Data Charges            7043 non-null   int64
 29  Total Long Distance Charges         7043 non-null   float64
 30  Total Revenue                       7043 non-null   float64
dtypes: float64(6), int64(5), object(20)
memory usage: 1.7+ MB
```

In [19]:

```python
services_df.isna().sum()
```

Out[19]:

```
Service ID                           0
Customer ID                          0
Count                                0
Quarter                              0
Referred a Friend                    0
Number of Referrals                  0
Tenure in Months                     0
Offer                                0
Phone Service                        0
Avg Monthly Long Distance Charges    0
Multiple Lines                       0
Internet Service                     0
Internet Type                        0
Avg Monthly GB Download              0
Online Security                      0
Online Backup                        0
Device Protection Plan               0
Premium Tech Support                 0
Streaming TV                         0
Streaming Movies                     0
Streaming Music                      0
Unlimited Data                       0
Contract                             0
Paperless Billing                    0
Payment Method                       0
Monthly Charge                       0
Total Charges                        0
Total Refunds                        0
Total Extra Data Charges             0
Total Long Distance Charges          0
Total Revenue                        0
dtype: int64
```

As a final step in our data understanding, we will remove any columns that are unnecessary or contain information that we already have in our other two available dataframes. This way, we will prevent overlapping of information and inaccurate feature dataframes. This way, we will prevent overlapping of information and inaccurate feature impact on our modeling later. Once again there are many columns in this dataframe that were repeated in the first (or second) dataframe, and therefore are unnecessary. Furthermore, any of the quarter or count information isn't relevant to our modeling process. These things have nothing to do with whether or not a customer churned, because no consumer is keeping track of fiscal quarters of their cellphone company to plan to cut their service, but gender or tenure with company might very well be relevant.

In [20]:
```
services_df = services_df.drop(['Service ID', 'Count', 'Quarter', 'Tenure in M
```

In [21]:
```
services_df
```

Out[21]:

	Customer ID	Referred a Friend	Number of Referrals	Offer	Avg Monthly Long Distance Charges	Internet Type	Avg Monthly GB Download	Streaming Music
0	8779-QRDMV	No	0	None	0.00	DSL	8	No
1	7495-OOKFY	Yes	1	Offer E	48.85	Fiber Optic	17	No
2	1658-BYGOY	No	0	Offer D	11.33	Fiber Optic	52	Yes
3	4598-XLKNJ	Yes	1	Offer C	19.76	Fiber Optic	12	No
4	4846-WHAFZ	Yes	1	Offer C	6.33	Fiber Optic	14	No
...	...	...	...	...	...	...	...	...
7038	2569-WGERO	No	0	None	22.77	None	0	No
7039	6840-RESVB	Yes	1	Offer C	36.05	Cable	24	Yes
7040	2234-XADUH	Yes	4	None	29.66	Fiber Optic	59	Yes
7041	4801-JZAZL	Yes	1	None	0.00	DSL	17	No
7042	3186-AJIEK	No	0	None	30.96	Fiber Optic	11	Yes

7043 rows × 15 columns

In [22]:
```
services_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 15 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
```

```
 0   Customer ID                        7043 non-null   object
 1   Referred a Friend                  7043 non-null   object
 2   Number of Referrals                7043 non-null   int64
 3   Offer                              7043 non-null   object
 4   Avg Monthly Long Distance Charges  7043 non-null   float64
 5   Internet Type                      7043 non-null   object
 6   Avg Monthly GB Download            7043 non-null   int64
 7   Streaming Music                    7043 non-null   object
 8   Unlimited Data                     7043 non-null   object
 9   Monthly Charge                     7043 non-null   float64
 10  Total Charges                      7043 non-null   float64
 11  Total Refunds                      7043 non-null   float64
 12  Total Extra Data Charges           7043 non-null   int64
 13  Total Long Distance Charges        7043 non-null   float64
 14  Total Revenue                      7043 non-null   float64
dtypes: float64(6), int64(3), object(6)
memory usage: 825.5+ KB
```

In [23]:

```
services_df.isna().sum()
```

Out[23]:

```
Customer ID                          0
Referred a Friend                    0
Number of Referrals                  0
Offer                                0
Avg Monthly Long Distance Charges    0
Internet Type                        0
Avg Monthly GB Download              0
Streaming Music                      0
Unlimited Data                       0
Monthly Charge                       0
Total Charges                        0
Total Refunds                        0
Total Extra Data Charges             0
Total Long Distance Charges          0
Total Revenue                        0
dtype: int64
```

Now, throughout all this data exploration and preparation, we have created three separate dataframes with one common column ("Customer ID"), 7043 entries that correspond to each other in each of the three dataframes, and various information on their services, plans, and habits. At this point, we must weld together those three separate dataframes into one usable one, and then begin the analysis process.

In [24]:

```
churn_df_2 = churn_df.merge(telco_churn, how="inner", on='Customer ID')
```

In [25]:

```
churn_df_2
```

Out[25]:

	Customer ID	Senior Citizen	Partner	Dependents	Tenure	Phone Service	Multiple Lines	Internet Service	S
0	7590-VHVEG	No	Yes	No	1	No	No phone service	DSL	
1	5575-GNVDE	No	No	No	34	Yes	No	DSL	
2	3668-QPYBK	No	No	No	2	Yes	No	DSL	
	7795-						No		

3	7795-CFOCW	No	No	No	45	No	No phone service	DSL
4	9237-HQITU	No	No	No	2	Yes	No	Fiber optic
...	...	...	...	...	...	...	...	...
7038	6840-RESVB	No	Yes	Yes	24	Yes	Yes	DSL
7039	2234-XADUH	No	Yes	Yes	72	Yes	Yes	Fiber optic
7040	4801-JZAZL	No	Yes	Yes	11	No	No phone service	DSL
7041	8361-LTMKD	Yes	Yes	No	4	Yes	Yes	Fiber optic
7042	3186-AJIEK	No	No	No	66	Yes	No	Fiber optic

7043 rows × 22 columns

In [26]:

```
churn_df_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7043 entries, 0 to 7042
Data columns (total 22 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   Customer ID        7043 non-null   object
 1   Senior Citizen     7043 non-null   object
 2   Partner            7043 non-null   object
 3   Dependents         7043 non-null   object
 4   Tenure             7043 non-null   int64 
 5   Phone Service      7043 non-null   object
 6   Multiple Lines     7043 non-null   object
 7   Internet Service   7043 non-null   object
 8   Online Security    7043 non-null   object
 9   Online Backup      7043 non-null   object
 10  Device Protection  7043 non-null   object
 11  Tech Support       7043 non-null   object
 12  Streaming TV       7043 non-null   object
 13  Streaming Movies   7043 non-null   object
 14  Contract           7043 non-null   object
 15  Paperless Billing  7043 non-null   object
 16  Payment Method     7043 non-null   object
 17  Churn              7043 non-null   object
 18  Gender             7043 non-null   object
 19  Churn Value        7043 non-null   int64 
 20  Churn Score        7043 non-null   int64 
 21  CLTV               7043 non-null   int64 
dtypes: int64(4), object(18)
memory usage: 1.2+ MB
```

Our final step in merging these dataframes is to combine the dataframe we just made with the third and final dataframe to create one fully meshed dataset that we can then use for modeling. Because of the steps we took during this preprocessing and exploration, we now have no nulls and properly arranged data, to make the process of modeling much easier going forward.

In [27]:
```
final_df = churn_df_2.merge(services_df, how="inner", on='Customer ID')
```

In [28]:
```
final_df
```

Out[28]:

	Customer ID	Senior Citizen	Partner	Dependents	Tenure	Phone Service	Multiple Lines	Internet Service	Se
0	7590-VHVEG	No	Yes	No	1	No	No phone service	DSL	
1	5575-GNVDE	No	No	No	34	Yes	No	DSL	
2	3668-QPYBK	No	No	No	2	Yes	No	DSL	
3	7795-CFOCW	No	No	No	45	No	No phone service	DSL	
4	9237-HQITU	No	No	No	2	Yes	No	Fiber optic	
...	...	...	...	...	...	...	...	...	
7038	6840-RESVB	No	Yes	Yes	24	Yes	Yes	DSL	
7039	2234-XADUH	No	Yes	Yes	72	Yes	Yes	Fiber optic	
7040	4801-JZAZL	No	Yes	Yes	11	No	No phone service	DSL	
7041	8361-LTMKD	Yes	Yes	No	4	Yes	Yes	Fiber optic	
7042	3186-AJIEK	No	No	No	66	Yes	No	Fiber optic	

7043 rows × 36 columns

In [29]:
```
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7043 entries, 0 to 7042
Data columns (total 36 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   Customer ID                       7043 non-null   object
 1   Senior Citizen                    7043 non-null   object
 2   Partner                           7043 non-null   object
 3   Dependents                        7043 non-null   object
 4   Tenure                            7043 non-null   int64
```

```
 5   Phone Service                      7043 non-null   object 
 6   Multiple Lines                     7043 non-null   object 
 7   Internet Service                   7043 non-null   object 
 8   Online Security                    7043 non-null   object 
 9   Online Backup                      7043 non-null   object 
 10  Device Protection                  7043 non-null   object 
 11  Tech Support                       7043 non-null   object 
 12  Streaming TV                       7043 non-null   object 
 13  Streaming Movies                   7043 non-null   object 
 14  Contract                           7043 non-null   object 
 15  Paperless Billing                  7043 non-null   object 
 16  Payment Method                     7043 non-null   object 
 17  Churn                              7043 non-null   object 
 18  Gender                             7043 non-null   object 
 19  Churn Value                        7043 non-null   int64  
 20  Churn Score                        7043 non-null   int64  
 21  CLTV                               7043 non-null   int64  
 22  Referred a Friend                  7043 non-null   object 
 23  Number of Referrals                7043 non-null   int64  
 24  Offer                              7043 non-null   object 
 25  Avg Monthly Long Distance Charges  7043 non-null   float64
 26  Internet Type                      7043 non-null   object 
 27  Avg Monthly GB Download            7043 non-null   int64  
 28  Streaming Music                    7043 non-null   object 
 29  Unlimited Data                     7043 non-null   object 
 30  Monthly Charge                     7043 non-null   float64
 31  Total Charges                      7043 non-null   float64
 32  Total Refunds                      7043 non-null   float64
 33  Total Extra Data Charges           7043 non-null   int64  
 34  Total Long Distance Charges        7043 non-null   float64
 35  Total Revenue                      7043 non-null   float64
dtypes: float64(6), int64(7), object(23)
memory usage: 2.0+ MB
```

Et voila! One "perfect" dataframe with many various features that can be used to compare against "Churn" and "Churn Value", respectively, in order to determine how much of an impact those features have on whether a customer will or will not churn. As a final last prepatory step before we continue, we will remove the "Customer ID" column before we begin to model, as it is not necessary and will trip up our model. I have also chosen to remove "CLTV" and "Churn Score" as I was not able to do the extraneous research needed to explain these features and the impact they might have on whether a customer churned or not.

In [30]:

```
final_df = final_df.drop(['Customer ID', 'Churn Value', 'Churn Score', 'CLTV']
```

In [31]:

```
final_df
```

Out[31]:

	Senior Citizen	Partner	Dependents	Tenure	Phone Service	Multiple Lines	Internet Service	Online Security	On Bac
0	No	Yes	No	1	No	No phone service	DSL	No	
1	No	No	No	34	Yes	No	DSL	Yes	
2	No	No	No	2	Yes	No	DSL	Yes	
3	No	No	No	45	No	No phone	DSL	Yes	

						service		
4	No	No	No	2	Yes	No	Fiber optic	No
...	...	...	...	...	...	...	...	...
7038	No	Yes	Yes	24	Yes	Yes	DSL	Yes
7039	No	Yes	Yes	72	Yes	Yes	Fiber optic	No
7040	No	Yes	Yes	11	No	No phone service	DSL	Yes
7041	Yes	Yes	No	4	Yes	Yes	Fiber optic	No
7042	No	No	No	66	Yes	No	Fiber optic	Yes

7043 rows × 32 columns

In [32]:

```
final_df['Churn'].value_counts(normalize=True)
```

Out[32]:

```
No     0.73463
Yes    0.26537
Name: Churn, dtype: float64
```

One very final thing to point out purely to help us better understand our data is that we do have a class imbalance. Of the customers we have available, some 7000 or so, 73% have not churned, while 27% have. This means that as we move into modeling our data, we must account for that class imbalance, because any models with be somewhat "safe" simply predicting that a customer will not churn, and that does not actually help in a business sense at all.

Analysis

Now it is time to establish correlation between our features (those 35 mentioned) and our target ("Churn") so that we can proceed with modeling those features against that target in order to predict whether a customer will churn with the highest possible recall. Remember that recall is our important metric here rather than accuracy because it measures, in this context, which customers are predicted to churn versus which customers actually churned.

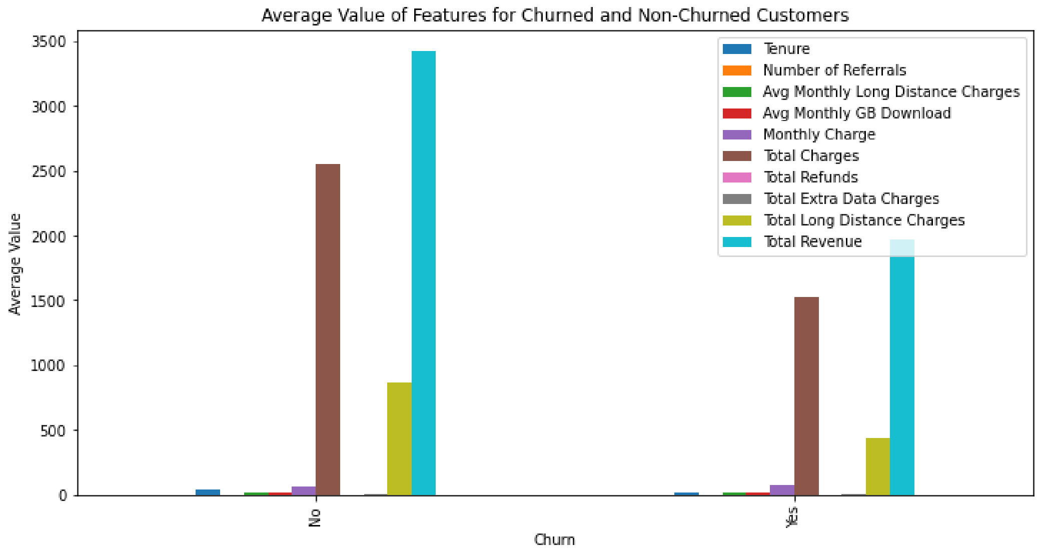
In [33]:

```
final_df_churn = final_df.groupby("Churn")

# Calculate the average value of each feature, separated by churn status
avg_values = final_df_churn.mean()

# Plot bar plots for each feature
avg_values.plot(kind="bar", figsize=(12, 6))
plt.xlabel("Churn")
plt.ylabel("Average Value")
plt.title("Average Value of Features for Churned and Non-Churned Customers")
plt.legend(loc="upper right")
plt.show()
```

```
plt.show()
```



As can be easily viewed from these bar charts, these features have a varying impact on whether or not a customer will churn, and should provide plenty of usable data for the purpose! From this, we begin to learn which features have the most impact on churn - in this case, total revenue, total charges and total long distance charges seem to be very important factors to whether or not a customer will churn, and that does make a lot of logical sense. If a customer has paid in a lot of money to a company ("Total Revenue"), they would be less likely to churn, as they've invested money. The "sunk cost fallacy" can explain this. To take things a logical step further, customers might also be more likely to churn (or not) if they are consistently charged extra for long distance or other features.

Now that we have established that our features do have some correlation as to whether or not a customer will churn, we can begin the modeling process with what might be our most important step - splitting our data into a test and training set, respectively. We do this because data leakage can cause a model to overperform. In other words, showing the test data to a model whilst it is training means that it is not truly telling us how well it performs on new data.

In [34]:

```
X = final_df.drop('Churn', axis=1)
y = final_df['Churn']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.25, rando
```

In [35]:

```
X_train
```

Out[35]:

	Senior Citizen	Partner	Dependents	Tenure	Phone Service	Multiple Lines	Internet Service	Online Security	Or Bac
6607	No	No	Yes	1	No	No phone service	DSL	No	
2598	No	No	No	7	Yes	No	Fiber optic	No	

2345	No	No	Yes	4	Yes	No	No	No internet service	inte se
4093	No	No	No	29	Yes	Yes	Fiber optic	No	
693	No	No	No	3	Yes	Yes	Fiber optic	No	
...	...	...	...	...	...	...	...	...	
3772	No	Yes	No	1	Yes	No	Fiber optic	Yes	
5191	No	Yes	Yes	23	Yes	Yes	DSL	Yes	
5226	No	Yes	Yes	12	Yes	No	No	No internet service	inte se
5390	Yes	No	No	12	Yes	Yes	Fiber optic	No	
860	No	No	No	26	Yes	No	No	No internet service	inte se

5282 rows × 31 columns

In [36]:

```
X_test
```

Out[36]:

	Senior Citizen	Partner	Dependents	Tenure	Phone Service	Multiple Lines	Internet Service	Online Security	Or Bac
185	No	Yes	No	1	No	No phone service	DSL	No	
2715	No	No	No	41	Yes	Yes	No	No internet service	inte se
3825	No	Yes	Yes	52	Yes	No	No	No internet service	inte se
1807	No	No	No	1	Yes	No	Fiber optic	No	
132	No	No	No	67	Yes	No	DSL	No	
...	...	...	...	...	...	...	...	...	
5845	No	No	No	3	Yes	Yes	Fiber optic	No	
2301	No	Yes	No	8	Yes	Yes	Fiber optic	No	
5121	No	No	No	29	Yes	Yes	DSL	No	
677	No	No	No	2	No	No phone	DSL	No	

						service		
6062	Yes	No	No	53	Yes	No	Fiber optic	No

1761 rows × 31 columns

Now, we will begin the modeling process by setting up a pipeline in order to scale our numerical features (such as Avg Monthly GB Download) to ensure that they are each taken with the same importance, and encoding our categorical features (such as Internet Service) to allow the model to parse through them properly. Many of our columns are actually Boolean, or "yes/no" data types, but they are listed as objects. Still, they will be able to be used in modeling just fine without any encoding, and we will not require any ordinal encoding as nothing here is in any sort of order. Essentially, the internet type ("Fiber optic", "DSL", or "no") has no listed order; there is no measurable numeric difference between "no" and "Fiber optic", so it does not need to be ordinally encoded.

In [37]:
```
le = LabelEncoder()
```

In [38]:
```
le.fit(y_train)
```

Out[38]:
```
LabelEncoder()
```

In [39]:
```
encoded_y_train = le.fit_transform(y_train)
```

In [40]:
```
encoded_y = le.transform(y_test)
```

In [41]:
```
le.classes_
```

Out[41]:
```
array(['No', 'Yes'], dtype=object)
```

In the above cells, I have had to establish a Label Encoder so that our target column, "Churn", will be registered as 0/1 rather than "no"/"yes", respectively. This will allow us to include the target column in the modeling process, which as I'm sure you can imagine is a very important thing to include!

In [42]:
```
num_feats = ['Tenure', 'Number of Referrals', 'Avg Monthly Long Distance Charg
cat_feats = ['Multiple Lines', 'Internet Service', 'Online Security', 'Online
ord_feats = ['Senior Citizen', 'Partner', 'Dependents', 'Phone Service', 'Pape
```

We've encoded "Gender" as male (0) and female (1).

In [43]:
```
X_train.columns
```

Out[43]:
```
Index(['Senior Citizen', 'Partner', 'Dependents', 'Tenure', 'Phone Service',
       'Multiple Lines', 'Internet Service', 'Online Security',
       'Online Backup', 'Device Protection', 'Tech Support', 'Streaming TV',
       'Streaming Movies', 'Contract', 'Paperless Billing', 'Payment Method',
       'Gender', 'Referred a Friend', 'Number of Referrals', 'Offer',
```

```
'Gender', 'Referred a Friend', 'Number of Referrals', 'Offer',
       'Avg Monthly Long Distance Charges', 'Internet Type',
       'Avg Monthly GB Download', 'Streaming Music', 'Unlimited Data',
       'Monthly Charge', 'Total Charges', 'Total Refunds',
       'Total Extra Data Charges', 'Total Long Distance Charges',
       'Total Revenue'],
      dtype='object')
```

In [44]:

```
prep_pipeline = ColumnTransformer(
    transformers=[
        ('categorical', OneHotEncoder(handle_unknown='ignore'), cat_feats),
        ('numeric', StandardScaler(), num_feats),
        ('other', OrdinalEncoder(categories=[['No', 'Yes'], ['No', 'Yes'], ['N
    ],
    remainder='passthrough')
```

In [45]:

```
X_train_encoded = prep_pipeline.fit_transform(X_train)
```

In [46]:

```
X_test_encoded = prep_pipeline.transform(X_test)
```

What we've done in the above cells is to create a pipeline that will OneHotEncode our categorical features and scale our numeric features, respectively, whilst leaving those that need no attention from the prep pipeline unchanged. At this point, we will instantiate a dummy model and run predictions on our training data. We have also LabelEncoded our target column to transform it from yes/no to 1/0, respectively, in order to make modeling possible.

In [47]:

```
dummy_model = DummyClassifier(strategy="most_frequent")
```

In [48]:

```
dummy_model.fit(X_train, y_train)
```

Out[48]:

```
DummyClassifier(strategy='most_frequent')
```

In [49]:

```
dummy_model.predict(X_train)[:50]
```

Out[49]:

```
array(['No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No'], dtype='<U2')
```

As stated, the dummy model has taken the most prevalent input from the 'Churn' target column and made that response its answer each time. In other words, the model has predicted that customers will not churn, because that is the most prevalent value in our target column. Now would be a good time to point out that we do have what is called a class imbalance, meaning that there are far more 'unchurned' customers than 'churned' ones to pull data from. We will be dealing with that throughout the process of modeling and analyzing, but for a dummy model, it is unnecessary to put that work in yet.

In [50]:

```
y.value_counts(normalize=True)
```

Out[50]:

```
No      0.73463
Yes     0.26537
```

```
Yes    0.26537
Name: Churn, dtype: float64
```

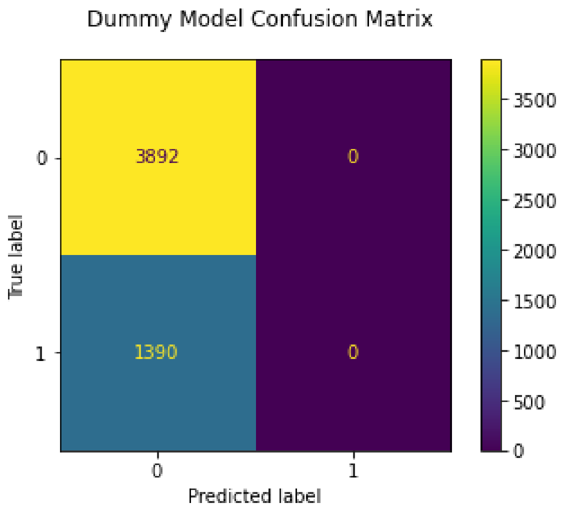
With all that in mind, let's see how well our dummy model performed!

In [51]:
```
fig, ax = plt.subplots()

fig.suptitle("Dummy Model Confusion Matrix")

ConfusionMatrixDisplay(confusion_matrix(y_train, dummy_model.predict(X_train))
```

Out[51]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2035555122
0>
```



In [52]:
```
cross_val_score(dummy_model, X_train, y_train, cv=5).mean()
```

Out[52]:
```
0.7368420486797971
```

At this point, our dummy model has a 73% accuracy score, and it will have 0% recall because it is a dummy model with no variation in its response - it predicts that a customer will not churn and it is correct 73% of the time. Obviously, 73% is not a very good score, and 0% is even worse, because remember that our biggest concern insofar as measurement metrics will be recall for this model. Therefore, the current score to beat is actually 0%, though we would love to see a better accuracy score as well.

First, we will instantiate a simple Decision Tree classifier to see if that alone performs better than our dummy model.

In [53]:
```
clf = tree.DecisionTreeClassifier()
```

In [54]:
```
clf.fit(X_train_encoded, encoded_y_train)
```

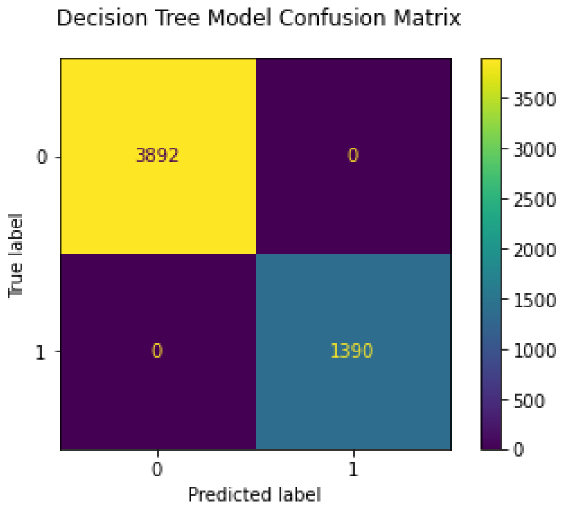
Out[54]:
```
DecisionTreeClassifier()
```

In [55]:
```
fig, ax = plt.subplots()

fig.suptitle("Decision Tree Model Confusion Matrix")

ConfusionMatrixDisplay(confusion_matrix(encoded_y_train, clf.predict(X_train_e
```

Out[55]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x20355977a90>



In [56]:
```
cross_val_score(clf, X_train_encoded, encoded_y_train, cv=5).mean()
```

Out[56]: 0.747444884034288

In [57]:
```
clf.score(X_train_encoded, encoded_y_train)
```

Out[57]: 1.0

As we can see, our simple decision tree is very overfit. Rather than try to fiddle with the very simple decision tree that will be unlikely to get us anywhere really, I have decided to move into random forest modeling and tweak that instead so that I can find the best model for this job.

In [58]:
```
rfc = RandomForestClassifier(random_state=42)
```

In [59]:
```
rfc.fit(X_train_encoded, encoded_y_train)
```

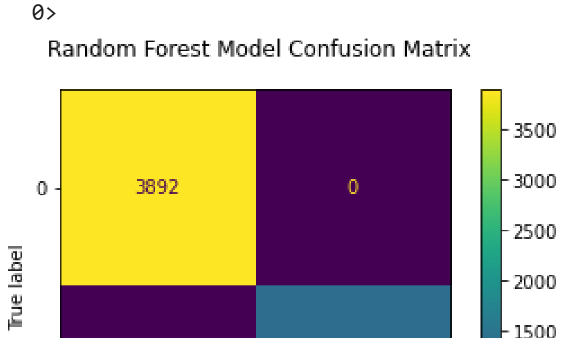
Out[59]: RandomForestClassifier(random_state=42)

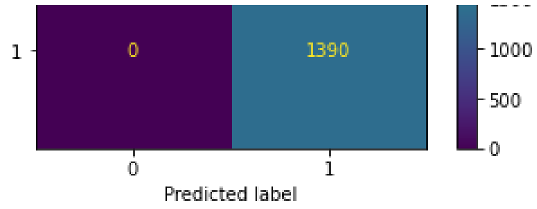
In [60]:
```
fig, ax = plt.subplots()

fig.suptitle("Random Forest Model Confusion Matrix")

ConfusionMatrixDisplay(confusion_matrix(encoded_y_train, rfc.predict(X_train_e
```

Out[60]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2035544af40>





In [61]:
```
cross_val_score(rfc, X_train_encoded, encoded_y_train, cv=5).mean()
```

Out[61]: 0.8152172744474069

In [62]:
```
rfc.score(X_train_encoded, encoded_y_train)
```

Out[62]: 1.0

As we may have guessed, an unaltered random forest model presents us with the exact same information as an even simpler decision tree model. Now, it's time to start hypertuning our random forest so that we can reduce overfitting and begin to accurately predict whether or not a customer will churn. We will need to tune our model, but also deal with the previously mentioned class imbalance in our data - most of the customers did not churn, and so our models are assuming that most people will not churn.

Another thing to note is that we have done these models outside of a pipeline, mainly because they are very simple models that I expected to both overfit and not predict very well. Thusly, it was not strictly "necessary" to establish a modeling pipeline for these very simple models. We will do that now, and use GridSearchCV to further tune our model.

In [63]:
```
model_pipeline = Pipeline(steps=[('preprocessing', prep_pipeline),
                                ('classifier', rfc)])
```

In [64]:
```
param_grid = {
    'classifier__n_estimators': [100, 200, 300],
    'classifier__max_depth': [None, 5, 10],
    'classifier__class_weight': [None, 'balanced', 'balanced_subsample']
}
```

In [65]:
```
param_grid2 = {
    'classifier__n_estimators': [90, 100, 110],
    'classifier__max_depth': [4, 5, 6],
    'classifier__class_weight': [None, 'balanced', 'balanced_subsample']
}
```

In the above cells, I have set up some parameter grids to allow us to hypertune our models and choose the best possible parameters to model with in order to achieve high recall and accuracy, though recall is our most important metric.

In [66]:
```
grid_search = GridSearchCV(estimator=model_pipeline, param_grid=param_grid, cv
```

In [67]:
```
grid_search.fit(X_train, encoded_y_train)
```

Out[67]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('preprocessing',
                                        ColumnTransformer(remainder='passthrou
gh',
                                                          transformers=[('cate
gorical',
                                                                         OneHo
tEncoder(handle_unknown='ignore'),
                                                                         ['Mul
tiple '
                                                                          'Lin
es',
                                                                          'Int
ernet '
                                                                          'Ser
vice',
                                                                          'Onl
ine '
                                                                          'Sec
urity',
                                                                          'Onl
ine '
                                                                          'Bac
kup',
                                                                          'Dev
ice '
                                                                          'Pro
tection',
                                                                          'Tec
h '
                                                                          'Sup
port',
                                                                          'Str
eaming '
                                                                          'T
V',
                                                                          'Str
eaming '
                                                                          'Mov
ies',
                                                                          'Con
tract',
                                                                          'Pay
ment '
                                                                          'Met
hod',

'O...
                                                                          'Dep
endents',
                                                                          'Pho
ne '
                                                                          'Ser
vice',
                                                                          'Pap
erless '
                                                                          'Bil
ling',
                                                                          'Gen
der',
                                                                          'Ref
erred '
                                                                          'a '
                                                                          'Fri
end',
                                                                          'Str
```

```
eaming '
                                                                            'Mus
ic',
                                                                            'Unl
imited '
                                                                            'Dat
a'])])),
                                        ('classifier',
                                         RandomForestClassifier(random_state=4
2))]),
             param_grid={'classifier__class_weight': [None, 'balanced',
                                                      'balanced_subsample'],
                         'classifier__max_depth': [None, 5, 10],
                         'classifier__n_estimators': [100, 200, 300]},
             scoring='recall')
```

In [68]:

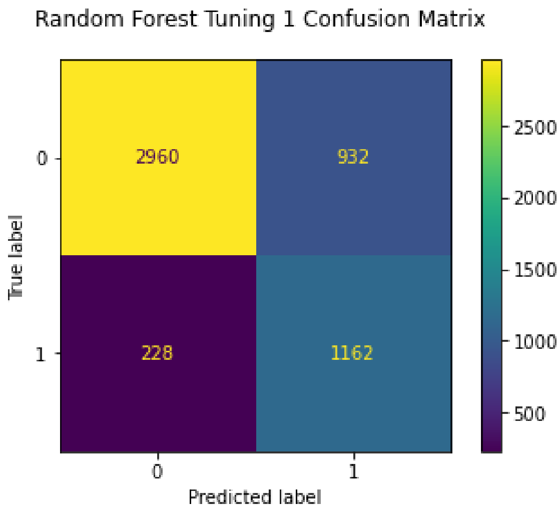
```
fig, ax = plt.subplots()

fig.suptitle("Random Forest Tuning 1 Confusion Matrix")

ConfusionMatrixDisplay(confusion_matrix(encoded_y_train, grid_search.predict(X
```

Out[68]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x20355519fd
0>
```



In [69]:

```
grid_search.best_score_
```

Out[69]:

```
0.8129496402877698
```

In [70]:

```
grid_search.score(X_train, encoded_y_train)
```

Out[70]:

```
0.8359712230215828
```

In [71]:

```
best_params1 = grid_search.best_params_
best_model1 = grid_search.best_estimator_
```

In [72]:

```
best_params1
```

Out[72]:

```
{'classifier__class_weight': 'balanced_subsample',
 'classifier__max_depth': 5,
 'classifier__n_estimators': 100}
```

After our first attempt at tuning our model, we have wound up with a slightly lower accuracy score, but our model is not as overfit. Furthermore, we have achieved a fairly decent recall score. Do recall (ba-dum-tss) that the reason "recall" is our most important metric is that recall shows whether a model can find all objects of the target class - in this case "churn". In other words, can this model find every possible churn case and help us prevent it? Earmarking potential churning customers is far more important than simply accurately predicting that they'll exist.

Now, we must use the hyperparameters given to us by our first attempt at tuning and see if we can't raise our recall, accuracy, or both!

In [73]:
```
grid_search2 = GridSearchCV(estimator=model_pipeline, param_grid=param_grid2,
```

In [74]:
```
grid_search2.fit(X_train, encoded_y_train)
```

Out[74]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('preprocessing',
                                        ColumnTransformer(remainder='passthrou
gh',
                                                          transformers=[('cate
gorical',
                                                                         OneHo
tEncoder(handle_unknown='ignore'),
                                                                         ['Mul
tiple '
                                                                          'Lin
es',
                                                                          'Int
ernet '
                                                                          'Ser
vice',
                                                                          'Onl
ine '
                                                                          'Sec
urity',
                                                                          'Onl
ine '
                                                                          'Bac
kup',
                                                                          'Dev
ice '
                                                                          'Pro
tection',
                                                                          'Tec
h '
                                                                          'Sup
port',
                                                                          'Str
eaming '
                                                                          'T
V',
                                                                          'Str
eaming '
                                                                          'Mov
ies',
                                                                          'Con
tract',
                                                                          'Pay
ment '
                                                                          'Met
hod',
```

```
'O...
                                                                                 'Par
tner',
                                                                                 'Dep
endents',
                                                                                 'Pho
ne '
                                                                                 'Ser
vice',
                                                                                 'Pap
erless '
                                                                                 'Bil
ling',
                                                                                 'Gen
der',
                                                                                 'Ref
erred '
                                                                                 'a '
                                                                                 'Fri
end',
                                                                                 'Str
eaming '
                                                                                 'Mus
ic',
                                                                                 'Unl
imited '
                                                                                 'Dat
a'])])),
                                        ('classifier',
                                         RandomForestClassifier(random_state=4
2))]),
             param_grid={'classifier__class_weight': [None, 'balanced',
                                                      'balanced_subsample'],
                         'classifier__max_depth': [4, 5, 6],
                         'classifier__n_estimators': [90, 100, 110]},
             scoring='recall')
```

In [75]:

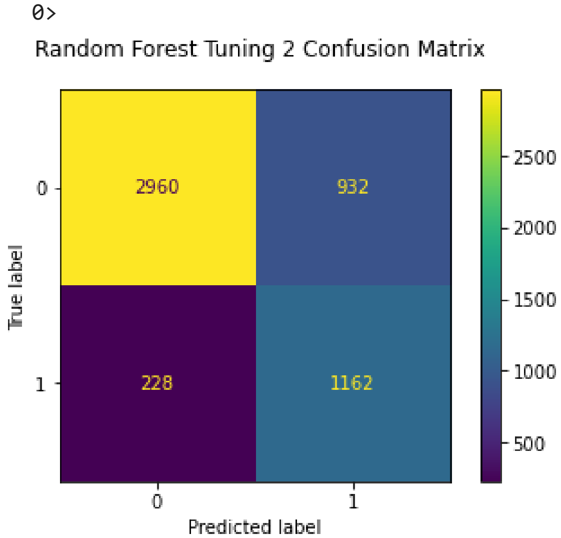
```python
fig, ax = plt.subplots()

fig.suptitle("Random Forest Tuning 2 Confusion Matrix")

ConfusionMatrixDisplay(confusion_matrix(encoded_y_train, grid_search2.predict(
```

Out[75]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x203555c4b8
0>
```



In [76]:

```python
best_params2 = grid_search.best_params_
best_model2 = grid_search.best_estimator
```

```
best_model2 = grid_search.best_estimator_
```

In [77]:
```
best_params2
```

Out[77]:
```
{'classifier__class_weight': 'balanced_subsample',
 'classifier__max_depth': 5,
 'classifier__n_estimators': 100}
```

In [78]:
```
grid_search2.best_score_
```

Out[78]:
```
0.8129496402877698
```

In [79]:
```
grid_search2.score(X_train, encoded_y_train)
```

Out[79]:
```
0.8359712230215828
```

In [80]:
```
ypred_final = grid_search2.predict(X_train)
```

In [81]:
```
ypred_final_test = grid_search2.predict(X_test)
```

In [82]:
```
accuracy_score(encoded_y, ypred_final_test)
```

Out[82]:
```
0.7745599091425327
```

In [83]:
```
recall_score(encoded_y, ypred_final_test)
```

Out[83]:
```
0.837160751565762
```

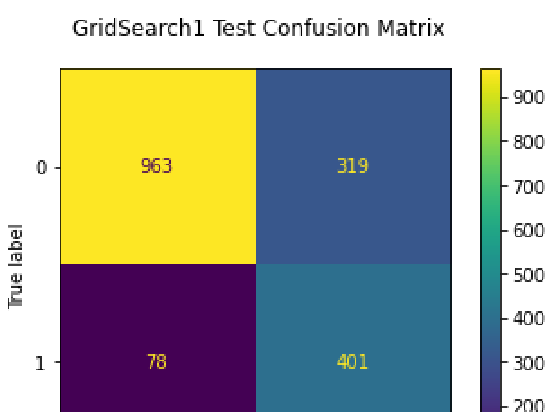
Our last model, here referred to as grid_search2, had a recall score of 84 and an accuracy score of 77. Due to this, our first tuning attempt turned out to be the more successful model, which is referred to as grid_search1. Here is a confusion matrix of gridsearch1 on the testing data.

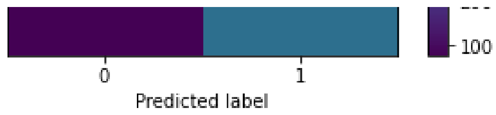
In [98]:
```
fig, ax = plt.subplots()

fig.suptitle("GridSearch1 Test Confusion Matrix")

ConfusionMatrixDisplay(confusion_matrix(encoded_y, grid_search.predict(X_test)
```

Out[98]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x20355050f1
0>
```





Our last analytic step is to determine feature importance within the model so that we can move forward with advisable next steps for our client. In other words, which of these features impacts customer churn the most? Or the least? Anyway, so I did a bit of a stupid and I did not set up the Capstone environment that we were advised to set up, meaning I am working with an outdated version of sklearn that makes it more difficult to get the feature importances from models. This is my own fault, and also allows me to showcase that I do know how to do it, even the hard way.

In [102…
```
feature_names = final_df.columns
```

In [103…
```
feature_names
```

Out[103…
```
Index(['Senior Citizen', 'Partner', 'Dependents', 'Tenure', 'Phone Service',
       'Multiple Lines', 'Internet Service', 'Online Security',
       'Online Backup', 'Device Protection', 'Tech Support', 'Streaming TV',
       'Streaming Movies', 'Contract', 'Paperless Billing', 'Payment Method',
       'Churn', 'Gender', 'Referred a Friend', 'Number of Referrals', 'Offer',
       'Avg Monthly Long Distance Charges', 'Internet Type',
       'Avg Monthly GB Download', 'Streaming Music', 'Unlimited Data',
       'Monthly Charge', 'Total Charges', 'Total Refunds',
       'Total Extra Data Charges', 'Total Long Distance Charges',
       'Total Revenue'],
      dtype='object')
```

In [104…
```
importance = best_model1.named_steps['classifier'].feature_importances_
```

In [105…
```
len(importance)
```

Out[105…
```
60
```

In [107…
```
best_model1.named_steps['preprocessing']
```

Out[107…
```
ColumnTransformer(remainder='passthrough',
                  transformers=[('categorical',
                                 OneHotEncoder(handle_unknown='ignore'),
                                 ['Multiple Lines', 'Internet Service',
                                  'Online Security', 'Online Backup',
                                  'Device Protection', 'Tech Support',
                                  'Streaming TV', 'Streaming Movies',
                                  'Contract', 'Payment Method', 'Offer',
                                  'Internet Type']),
                                ('numeric', StandardScaler(),
                                 ['Tenure', 'Number of Referrals...
                                  'Total Extra Data Charges',
                                  'Total Long Distance Charges',
                                  'Total Revenue']),
                                ('other',
                                 OrdinalEncoder(categories=[['No', 'Yes'],
                                                            ['No', 'Yes'],
                                                            ['No', 'Yes'],
                                                            ['No', 'Yes'],
                                                            ['No', 'Yes'],
                                                            ['Male', 'Femal
```

```
e'],
                                                              ['No', 'Yes'],
                                                              ['No', 'Yes'],
                                                              ['No', 'Yes']]),
                                 ['Senior Citizen', 'Partner', 'Dependents',
                                  'Phone Service', 'Paperless Billing',
                                  'Gender', 'Referred a Friend',
                                  'Streaming Music', 'Unlimited Data'])])
```

In [109…

```
ohe_ob = best_model1.named_steps['preprocessing'].named_transformers_['categor
```

In [110…

```
feature_names = list(ohe_ob.fit(final_df[cat_feats]).get_feature_names())
```

In [111…

```
feature_names.extend(num_feats)
```

In [112…

```
feature_names.extend(ord_feats)
```

In [113…

```
len(feature_names)
```

Out[113…

```
60
```

In [114…

```
feature_importance_dict = dict(zip(feature_names, importance))
```

In [115…

```
feature_importance_dict
```

Out[115…

```
{'x0_No': 0.0007536644088750889,
 'x0_No phone service': 0.00045462930063695333,
 'x0_Yes': 0.0012088887538025575,
 'x1_DSL': 0.010471131528028282,
 'x1_Fiber optic': 0.05605535990829115,
 'x1_No': 0.005828075900586288,
 'x2_No': 0.04308050128351848,
 'x2_No internet service': 0.010758660321975547,
 'x2_Yes': 0.009538193603015714,
 'x3_No': 0.010948717847090852,
 'x3_No internet service': 0.0071142202338824985,
 'x3_Yes': 0.0035219761947465813,
 'x4_No': 0.00550623506937089,
 'x4_No internet service': 0.012410124223649278,
 'x4_Yes': 0.0007705838082981888,
 'x5_No': 0.042529118139103324,
 'x5_No internet service': 0.01793669484824282,
 'x5_Yes': 0.009127110094486211,
 'x6_No': 0.0012623396709702493,
 'x6_No internet service': 0.010379730771566112,
 'x6_Yes': 0.001295866263891002,
 'x7_No': 0.0007621508683868874,
 'x7_No internet service': 0.006295363219339737,
 'x7_Yes': 0.00191331154499985,
 'x8_Month-to-month': 0.12434859554708974,
 'x8_One year': 0.012809908978589822,
 'x8_Two year': 0.08255887793348525,
```