

# Churn\_AdaBoost

April 23, 2024

```
[18]: # Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.preprocessing import MinMaxScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, \
    accuracy_score, f1_score
from sklearn.model_selection import GridSearchCV
from sklearn.feature_selection import RFE
from sklearn.ensemble import AdaBoostClassifier

import warnings
warnings.filterwarnings('ignore')

[7]: # Reading in the data
churn = pd.read_csv('/Users/gregory/Desktop/data_mining_2/Projects/Project_4/
    ↳Data/telco_churn_data_clean.csv')

churn.head()
```

```
[7]:
```

	Unnamed: 0	Referred_a_Friend	Number_of_Referrals	Tenure_in_Months	\
0	3	1	1	25	
1	4	1	1	37	
2	5	0	0	27	
3	6	1	1	1	
4	7	1	6	58	

	Offer	Phone_Service	Avg_Monthly_Long_Distance_Charges	Multiple_Lines	\
0	3.0	1	19.76	0	
1	3.0	1	6.33	1	
2	3.0	1	3.33	1	
3	5.0	1	15.28	0	

4	2.0	0	0.00	0
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	Internet_Service	Internet_Type	...	Married	Number_of_Dependents	\
0	1	1.0	...	1	1	
1	1	2.0	...	1	1	
2	1	1.0	...	0	1	
3	1	2.0	...	1	2	
4	1	2.0	...	1	0	

	Zip_Code	Population	Churn_Value	CLTV	Churn_Category	\
0	90303	27778	1	5337	2.0	
1	90602	26265	1	2793	3.0	
2	90660	63288	1	4638	1.0	
3	90720	21343	1	3964	5.0	
4	91024	10558	1	5444	2.0	

	Total_Customer_Svc_Requests	Product/Service_Issues_Reported	\
0	1	1	
1	1	0	
2	0	0	
3	7	0	
4	2	1	

	Customer_Satisfaction
0	2.0
1	2.0
2	2.0
3	1.0
4	1.0

[5 rows x 39 columns]

```
[8]: # Drop the unnamed column
```

```
churn2 = churn.drop('Unnamed: 0', axis = 1)

churn2.head()
```

	Referred_a_Friend	Number_of_Referrals	Tenure_in_Months	Offer	\
0	1	1	25	3.0	
1	1	1	37	3.0	
2	0	0	27	3.0	
3	1	1	1	5.0	
4	1	6	58	2.0	

	Phone_Service	Avg_Monthly_Long_Distance_Charges	Multiple_Lines	\
0	1	19.76	0	

1	1	6.33	1
2	1	3.33	1
3	1	15.28	0
4	0	0.00	0

	Internet_Service	Internet_Type	Avg_Monthly_GB_Download	...	Married	\
0	1	1.0	13	...	1	
1	1	2.0	15	...	1	
2	1	1.0	20	...	0	
3	1	2.0	33	...	1	
4	1	2.0	26	...	1	

	Number_of_Dependents	Zip_Code	Population	Churn_Value	CLTV	\
0	1	90303	27778	1	5337	
1	1	90602	26265	1	2793	
2	1	90660	63288	1	4638	
3	2	90720	21343	1	3964	
4	0	91024	10558	1	5444	

	Churn_Category	Total_Customer_Svc_Requests	\
0	2.0	1	
1	3.0	1	
2	1.0	0	
3	5.0	7	
4	2.0	2	

	Product/Service_Issues_Reported	Customer_Satisfaction
0	1	2.0
1	0	2.0
2	0	2.0
3	0	1.0
4	1	1.0

[5 rows x 38 columns]

```
[9]: # Moving target for ease of access

churn_val = churn2.pop('Churn_Value')
churn2.insert(37, "Churn_Value", churn_val)

churn2.head()
```

	Referred_a_Friend	Number_of_Referrals	Tenure_in_Months	Offer	\
0	1	1	25	3.0	
1	1	1	37	3.0	
2	0	0	27	3.0	
3	1	1	1	5.0	

4	1	6	58	2.0
---	---	---	----	-----

	Phone_Service	Avg_Monthly_Long_Distance_Charges	Multiple_Lines	\
0	1	19.76	0	
1	1	6.33	1	
2	1	3.33	1	
3	1	15.28	0	
4	0	0.00	0	

	Internet_Service	Internet_Type	Avg_Monthly_GB_Download	...	Married	\
0	1	1.0	13	...	1	
1	1	2.0	15	...	1	
2	1	1.0	20	...	0	
3	1	2.0	33	...	1	
4	1	2.0	26	...	1	

	Number_of_Dependents	Zip_Code	Population	CLTV	Churn_Category	\
0	1	90303	27778	5337	2.0	
1	1	90602	26265	2793	3.0	
2	1	90660	63288	4638	1.0	
3	2	90720	21343	3964	5.0	
4	0	91024	10558	5444	2.0	

	Total_Customer_Svc_Requests	Product/Service_Issues_Reported	\
0	1	1	
1	1	0	
2	0	0	
3	7	0	
4	2	1	

	Customer_Satisfaction	Churn_Value
0	2.0	1
1	2.0	1
2	2.0	1
3	1.0	1
4	1.0	1

[5 rows x 38 columns]

[13]: churn2

	Referred_a_Friend	Number_of_Referrals	Tenure_in_Months	Offer	\
0	1	1	25	3.0	
1	1	1	37	3.0	
2	0	0	27	3.0	
3	1	1	1	5.0	
4	1	6	58	2.0	

...	...	...	...	...
7035	0	0	72	3.4
7036	1	1	24	3.0
7037	1	4	72	3.0
7038	1	1	11	3.0
7039	0	0	66	3.0

	Phone_Service	Avg_Monthly_Long_Distance_Charges	Multiple_Lines	\
0	1	19.76	0	
1	1	6.33	1	
2	1	3.33	1	
3	1	15.28	0	
4	0	0.00	0	
...	...	...	...	
7035	1	22.77	0	
7036	1	36.05	1	
7037	1	29.66	1	
7038	0	0.00	0	
7039	1	30.96	0	

	Internet_Service	Internet_Type	Avg_Monthly_GB_Download	...	Married	\
0	1	1.0	13	...	1	
1	1	2.0	15	...	1	
2	1	1.0	20	...	0	
3	1	2.0	33	...	1	
4	1	2.0	26	...	1	
...	...	...	...	...	...	
7035	0	2.0	0	...	0	
7036	1	3.0	24	...	1	
7037	1	2.0	59	...	1	
7038	1	3.0	17	...	1	
7039	1	1.0	11	...	0	

	Number_of_Dependents	Zip_Code	Population	CLTV	Churn_Category	\
0	1	90303	27778	5337	2.0	
1	1	90602	26265	2793	3.0	
2	1	90660	63288	4638	1.0	
3	2	90720	21343	3964	5.0	
4	0	91024	10558	5444	2.0	
...	...	...	...	...	...	
7035	0	92285	2182	5306	1.0	
7036	2	92301	18980	2140	1.0	
7037	2	92304	42	5560	1.0	
7038	2	92305	301	2793	1.0	
7039	0	92308	28819	5097	1.0	

Total_Customer_Svc_Requests	Product/Service_Issues_Reported	\
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0	1	1
1	1	0
2	0	0
3	7	0
4	2	1
...	...	...
7035	0	0
7036	2	0
7037	2	0
7038	0	0
7039	1	2

	Customer_Satisfaction	Churn_Value
0	2.0	1
1	2.0	1
2	2.0	1
3	1.0	1
4	1.0	1
...	...	...
7035	4.0	0
7036	4.0	0
7037	4.0	0
7038	4.0	0
7039	4.0	0

[7040 rows x 38 columns]

```
[15]: # Split data

X = churn2.iloc[:, 0:37]
y = churn2.iloc[:, 37]

# Min-Max

mms = MinMaxScaler()
X_minmax = mms.fit_transform(X)

# Train/Test split

X_train, X_test, y_train, y_test = train_test_split(X_minmax, y, train_size=0.
↪8, stratify=y, random_state=0)
```

```
[17]: # GridSearchCV

parameters = {
    'n_estimators': [10, 50, 100],
    'learning_rate': [0.01, 0.1, 0.5, 1, 2]
```

```

}

ada = AdaBoostClassifier()
clf = GridSearchCV(ada, parameters)
clf.fit(X_train, y_train)
print(clf.best_estimator_)

```

```
AdaBoostClassifier(learning_rate=1, n_estimators=100)
```

```

[35]: # RFE

ada = AdaBoostClassifier(learning_rate=1, n_estimators=100)
selector = RFE(ada)
selector.fit(X_train,y_train)

X_train_rfe = selector.transform(X_train)
X_test_rfe = selector.transform(X_test)

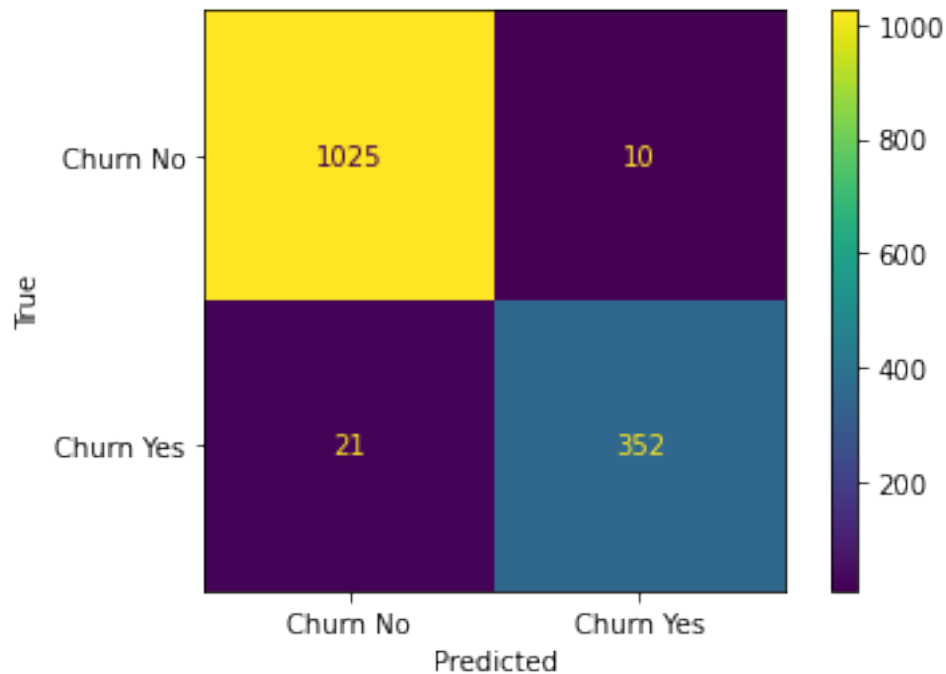
ada.fit(X_train_rfe, y_train)
y_pred = ada.predict(X_test_rfe)

cf_matrix = confusion_matrix(y_test,y_pred)
cmd = ConfusionMatrixDisplay(cf_matrix, display_labels=['Churn No', 'Churn_
↳Yes'])
cmd.plot()
cmd.ax_.set(xlabel='Predicted', ylabel='True')

f1_score(y_test,y_pred) # 95.78%

```

```
[35]: 0.9578231292517007
```



```
[37]: # Feature Names
X_train_df = pd.DataFrame(data=X_train)
features = selector.fit_transform(X_train,y_train)
feature_idx = selector.get_support(indices=True)
feature_names = X_train_df.columns[feature_idx]
features = pd.DataFrame(features, columns=feature_names)
features.head()

# Selected Predictors:

# 1: Number_of_Referrals
# 2: Tenure_in_Months
# 3: Offer
# 5: Avg_Monthly_Long_Distance_Charges
# 8: Internet_Type
# 9: Avg_Monthly_GB_Download
# 20: Payment_Method
# 21: Monthly_Charge
# 22: Total_Regular_Charges
# 24: Total_Extra_Data_Charges
# 25: Total_Long_Distance_Charges
# 29: Number_of_Dependents
# 30: Zip_Code
# 31: Population
# 32: CLTV
```



```
# 34: Total_Customer_Svc_Requests
# 35: Product/Service_Issues_Reported
# 36: Customer_Satisfaction
```

```
[37]:
```

	1	2	3	5	8	9	20	21	\
0	0.000000	0.253521	0.75	0.343469	0.20	0.000000	0.5	0.005246	
1	0.454545	1.000000	0.00	0.427485	1.00	0.138298	0.0	0.932903	
2	0.272727	0.619718	0.25	0.616123	1.00	0.031915	0.5	0.630521	
3	0.000000	0.014085	1.00	0.879376	0.50	0.159574	0.0	0.605166	
4	0.000000	0.154930	0.75	0.779356	0.25	0.000000	0.5	0.017170	

	22	24	25	29	30	31	32	34	\
0	0.030048	0.000000	0.091516	0.0	0.213043	0.335448	0.203024	0.222222	
1	0.967701	0.000000	0.431630	0.0	0.383477	0.069466	0.533911	0.333333	
2	0.443024	0.000000	0.388810	0.0	0.915921	0.023985	0.311319	0.000000	
3	0.015088	0.003397	0.024664	0.0	0.498455	0.028070	0.711586	0.000000	
4	0.028462	0.000000	0.131152	0.0	0.419743	0.042223	0.665555	0.000000	

	35	36
0	0.000000	0.75
1	0.166667	0.50
2	0.000000	0.50
3	0.000000	0.25
4	0.000000	1.00

```
[ ]:
```