churnproj

July 28, 2023

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Spring 2023 - Customer Churn Prediction Analysis

[1]:
```
# Libraries
# General
import pandas as pd
import numpy as np

# ML
from sklearn.model_selection import train_test_split
import statsmodels.formula.api as smf
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪accuracy_score, roc_curve, auc
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.preprocessing import OneHotEncoder

# Viz
import matplotlib.pyplot as plt
from importlib import *
import plotly.express as px
import matplotlib.patches as patches
```

This dataset includes information about cellphone company customers and whether they stayed or left the company (churn)

Note: Data Cleaning has been performed prior to this step

[2]:
```
# Dataset: customerchurn.csv
churn = pd.read_csv("customerchurn.csv")
churn.info()
churn
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7032 entries, 0 to 7031
Data columns (total 7 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Churn             7032 non-null   int64
```

```
 1   MonthlyCharges   7032 non-null   float64
 2   SeniorCitizen    7032 non-null   int64
 3   PaymentMethod    7032 non-null   object
 4   InternetService  7032 non-null   object
 5   tenure           7032 non-null   int64
 6   Contract         7032 non-null   object
dtypes: float64(1), int64(3), object(3)
memory usage: 384.7+ KB
```

[2]:

```
      Churn  MonthlyCharges  SeniorCitizen     PaymentMethod InternetService  \
0         0           29.85              0  Electronic check             DSL
1         0           56.95              0      Mailed check             DSL
2         1           53.85              0      Mailed check             DSL
3         0           42.30              0     Bank transfer             DSL
4         1           70.70              0  Electronic check     Fiber optic
…       …             …            …               …             …
7027      0           84.80              0      Mailed check             DSL
7028      0          103.20              0       Credit card     Fiber optic
7029      0           29.60              0  Electronic check             DSL
7030      1           74.40              1      Mailed check     Fiber optic
7031      0          105.65              0     Bank transfer     Fiber optic

      tenure        Contract
0          1  Month-to-month
1         34        One year
2          2  Month-to-month
3         45        One year
4          2  Month-to-month
…        …             …
7027      24        One year
7028      72        One year
7029      11  Month-to-month
7030       4  Month-to-month
7031      66        Two year

[7032 rows x 7 columns]
```

[3]:

```python
# Dependent variable: Churn 0 (no churn) or 1 (churn)
# Independent variables: 6
X = churn.drop(['Churn'], axis=1)
y = churn['Churn']
print(X.shape), print(y.shape)
```

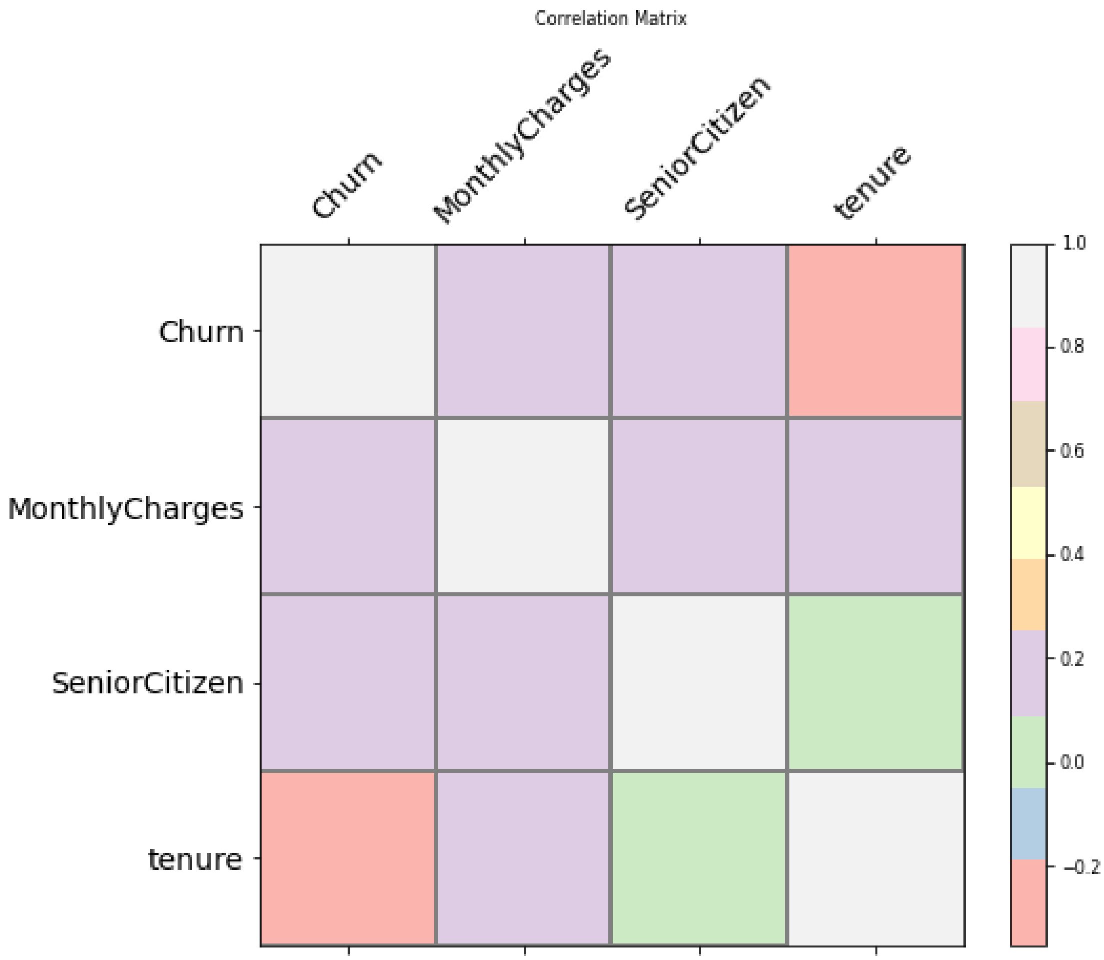
```
(7032, 6)
(7032,)
```

[3]: (None, None)

0.0.1 EDA

[4]:
```
# some EDA

# Null value check
nullvals = churn.isnull().sum()
print('Null values in each col:\n', nullvals)


f = plt.figure(figsize=(8, 6))
# Creating a gradient colormap based on 'Pastel1'
pastel1 = plt.get_cmap('Pastel1')
n = len(churn.columns)
gradient_colors = pastel1(np.linspace(0, 1, n**2))

# Create a new colormap from the gradient colors
gradient_cmap = plt.matplotlib.colors.LinearSegmentedColormap.
 ↪from_list('pastel1_gradient', gradient_colors, n**2)

plt.matshow(churn.corr(), fignum=f.number, cmap=gradient_cmap)
plt.xticks(range(churn.select_dtypes(['number']).shape[1]), churn.
 ↪select_dtypes(['number']).columns, fontsize=14, rotation=45)
plt.yticks(range(churn.select_dtypes(['number']).shape[1]), churn.
 ↪select_dtypes(['number']).columns, fontsize=14)
cb = plt.colorbar()
cb.ax.tick_params(labelsize=8)

# Black Borders
for i in range(len(churn.corr())):
    for j in range(len(churn.corr())):
        if i != j:
            plt.gca().add_patch(patches.Rectangle((i - 0.5, j - 0.5), 1, 1,␣
 ↪fill=False, edgecolor='gray', lw=2))

plt.title('Correlation Matrix', fontsize=8)
plt.show()
```

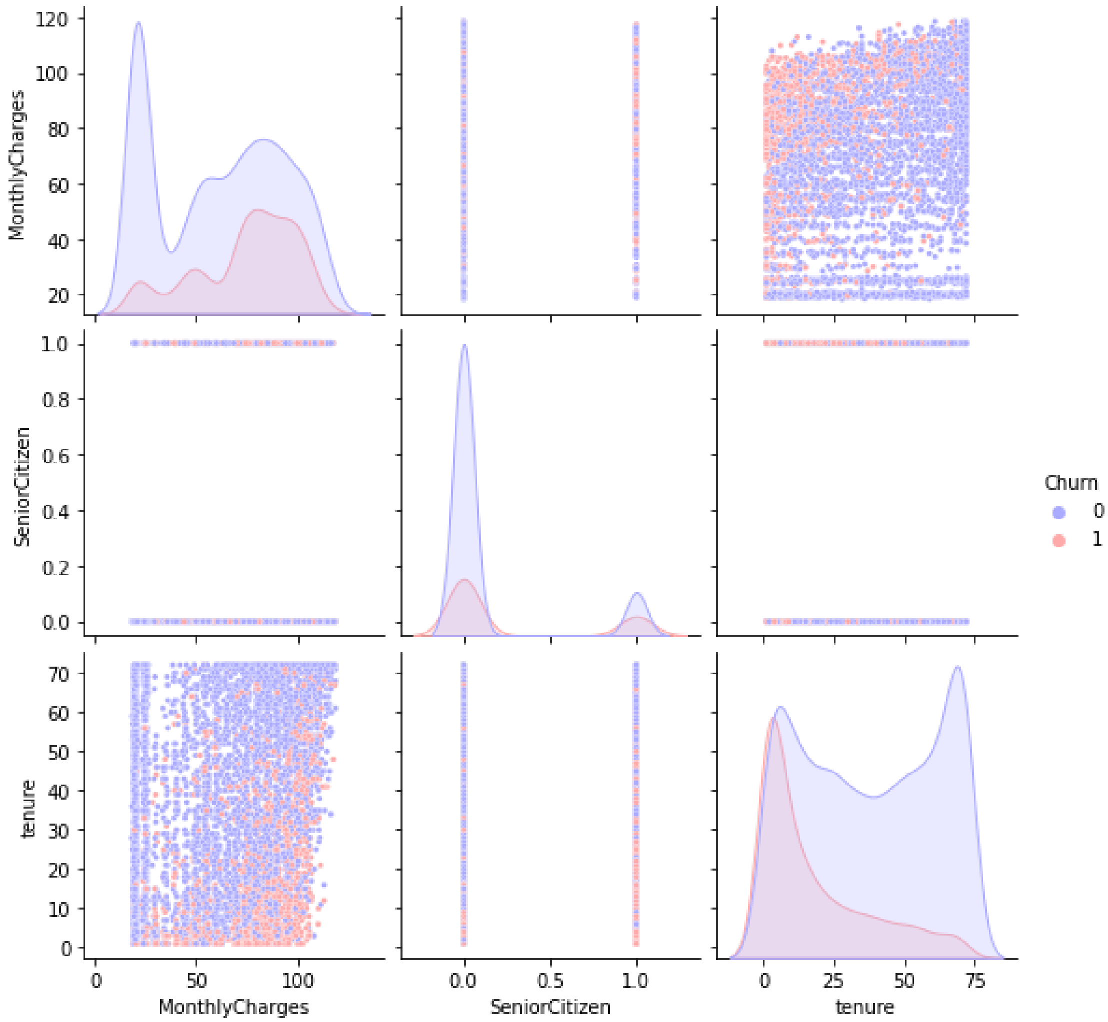
```
Null values in each col:
 Churn              0
MonthlyCharges     0
SeniorCitizen      0
PaymentMethod      0
InternetService    0
tenure             0
Contract           0
dtype: int64
```




```
[5]: # Using seaborn to plot scatter plot for continuous variables
import seaborn as sns
sns.pairplot(churn, diag_kind='kde', height=2.6, hue='Churn', palette='bwr',␣
 ↪plot_kws=dict(s=10))
```

```
/opt/homebrew/lib/python3.9/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
[5]: <seaborn.axisgrid.PairGrid at 0x1668afd60>
```



[6]:
```
color_map = {1: '#FFB3B3', 0: '#D2DAFF'}
fig = px.histogram(churn, x="Churn", color="SeniorCitizen",␣
 ↪title="<b>Distribution Chart of Senior Citizens & Churn Rate</b>",␣
 ↪color_discrete_map=color_map)
fig.update_layout(width=500, height=400, bargap=0.1)
fig.update_traces(marker_line_color='gray', marker_line_width=1.5)

fig.show()
```

[7]:
```
senior_churn = churn[churn['SeniorCitizen'] == 1]
senior = senior_churn['Churn'].value_counts()
senior[1] / (senior[0] + senior[1])
seniorYes = senior_churn[senior_churn['Churn'] == 1]
seniorNo = senior_churn[senior_churn['Churn'] == 0]
total = len(seniorYes) / (len(seniorYes) + len(seniorNo))
```

```
print('In total, approximately: ', round(total, 2) * 100, ' % of senior␣
↪citizens churned')
```

```
In total, approximately:  42.0  % of senior citizens churned
```

[8]:
```
show = churn[churn['Churn'] == 1]
seniorchurn = show[show['SeniorCitizen'] == 1]
seniorchurn
```

[8]:
```
      Churn  MonthlyCharges  SeniorCitizen     PaymentMethod InternetService  \
20        1           39.65              1  Electronic check             DSL
53        1           80.65              1       Credit card     Fiber optic
55        1           95.45              1  Electronic check     Fiber optic
99        1           98.50              1  Electronic check     Fiber optic
113       1           76.50              1  Electronic check     Fiber optic
…       …             …             …               …             …
6982      1           88.05              1  Electronic check     Fiber optic
6997      1           75.05              1       Credit card     Fiber optic
6999      1           74.45              1  Electronic check     Fiber optic
7021      1           75.75              1  Electronic check     Fiber optic
7030      1           74.40              1      Mailed check     Fiber optic

      tenure        Contract
20         1  Month-to-month
53         8  Month-to-month
55        18  Month-to-month
99        25  Month-to-month
113       37  Month-to-month
…        …             …
6982      50  Month-to-month
6997       3  Month-to-month
6999       1  Month-to-month
7021       1  Month-to-month
7030       4  Month-to-month

[476 rows x 7 columns]
```

Notes on above EDA:

- We can see that monthly charges are not a huge identifier of a customer churning or not - as we have many customers with high monthly charges that have not churned.
- Of the 1,393 customers that churned, 476 of them were senior citizens.
- Of the 1,142 seniors in the dataset, 476 of them churned which is a very high churn rate for senior citizens. (41%)
- Tenure has a negative correlation with churn as we can also see from both the correlation matrix above & our pairplot
- When Tenure is low, and monthly charges are high, we can visually identify a high churn rate

[9]:
```
# Splitting train/test
train, test = train_test_split(churn, test_size=0.3, random_state=42)
train.shape, test.shape
```

[9]: ((4922, 7), (2110, 7))

Baseline Accuracy - Predict the most common output feature

[10]:
```
baseline = y.value_counts()[0]/len(y)
print('Baseline Accuracy:', round(baseline, 3) * 100,'%')
```

```
Baseline Accuracy: 73.4 %
```

[11]:
```
# Variable Selecting & model fitting
logreg = smf.logit(formula = 'Churn ~ MonthlyCharges + SeniorCitizen +␣
 ↪PaymentMethod + InternetService + tenure + Contract',
                       data = train).fit()
print(logreg.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.421207
         Iterations 8
                           Logit Regression Results
==============================================================================
Dep. Variable:                  Churn   No. Observations:                 4922
Model:                          Logit   Df Residuals:                     4911
Method:                           MLE   Df Model:                           10
Date:                Fri, 28 Jul 2023   Pseudo R-squ.:                  0.2725
Time:                        17:56:54   Log-Likelihood:                -2073.2
converged:                       True   LL-Null:                       -2849.7
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
=====================
                                        coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------------------
---------------------
Intercept                            -0.6747      0.214     -3.157      0.002
-1.094      -0.256
PaymentMethod[T.Credit card]         -0.1505      0.135     -1.115      0.265
-0.415       0.114
PaymentMethod[T.Electronic check]     0.3186      0.111      2.865      0.004
0.101       0.537
PaymentMethod[T.Mailed check]        -0.1227      0.134     -0.915      0.360
-0.385       0.140
InternetService[T.Fiber optic]        0.9479      0.156      6.059      0.000
0.641       1.255
InternetService[T.No]                -0.7120      0.182     -3.910      0.000
```

```
-1.069      -0.355
Contract[T.One year]                    -0.8964      0.128     -7.006      0.000
-1.147      -0.646
Contract[T.Two year]                    -1.5712      0.202     -7.760      0.000
-1.968      -1.174
MonthlyCharges                           0.0048      0.004      1.293      0.196
-0.002       0.012
SeniorCitizen                            0.3610      0.098      3.677      0.000
0.169       0.553
tenure                                  -0.0322      0.003    -12.417      0.000
-0.037      -0.027
================================================================================
=====================
```

Notes / Interpretation on Logit Regression Results:

- Our * p > |z| * value for payment method is large (0.265, 0.360)
- So I am going to create a column that only includes Electronic Check as payment method as Credit card & mailed check can be contributing to high variance inflation factors and should therefore be removed for a better fit model.

[12]:

```python
# Remove PaymentMethod Credit Card & Payment Method Mailed check.
# Create a new feature (dummy var)
train2 = train.copy()
train2['ElectronicCheck'] = (train2['PaymentMethod'] == 'Electronic check').
 ↪astype('int64')
train2.drop(columns=['PaymentMethod'], inplace=True)

# Repeat for test set as well
test2 = test.copy()
test2['ElectronicCheck'] = (test2['PaymentMethod'] == 'Electronic check').
 ↪astype('int64')
test2.drop(columns=['PaymentMethod'], inplace=True)

test2.head()
```

[12]:

```
      Churn  MonthlyCharges  SeniorCitizen InternetService  tenure  \
2476      0           25.00              1              No      61
6773      0           24.70              0              No      19
6116      1          102.25              0     Fiber optic      13
3047      0           55.05              0             DSL      37
4092      0           29.45              0             DSL       6

            Contract  ElectronicCheck
2476        Two year                0
6773  Month-to-month                0
6116  Month-to-month                0
3047  Month-to-month                0
```

```
4092  Month-to-month                 0
```

[13]:
```
test2['ElectronicCheck'].value_counts()
```

[13]:
```
0    1418
1     692
Name: ElectronicCheck, dtype: int64
```

[14]:
```
logreg2 = smf.logit(formula = 'Churn ~ SeniorCitizen + ElectronicCheck +␣
 ↪InternetService + tenure + Contract',
                          data = train2).fit()
print(logreg2.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.421529
         Iterations 8
                           Logit Regression Results
==============================================================================
Dep. Variable:                  Churn   No. Observations:                 4922
Model:                          Logit   Df Residuals:                     4914
Method:                           MLE   Df Model:                            7
Date:                Fri, 28 Jul 2023   Pseudo R-squ.:                  0.2719
Time:                        17:56:55   Log-Likelihood:                -2074.8
converged:                       True   LL-Null:                       -2849.7
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
==================
                                    coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------------------
------------------
Intercept                        -0.5498      0.085     -6.465      0.000
-0.716      -0.383
InternetService[T.Fiber optic]    1.1192      0.090     12.471      0.000
0.943       1.295
InternetService[T.No]            -0.8659      0.141     -6.120      0.000
-1.143      -0.589
Contract[T.One year]             -0.8797      0.127     -6.936      0.000
-1.128      -0.631
Contract[T.Two year]             -1.5495      0.201     -7.703      0.000
-1.944      -1.155
SeniorCitizen                     0.3587      0.098      3.656      0.000
0.166       0.551
ElectronicCheck                   0.4130      0.081      5.100      0.000
0.254       0.572
tenure                           -0.0308      0.002    -12.923      0.000
-0.035      -0.026
```

===
==================

Notes on above Logit Regression results: - Now we can see that all of the p-values are close to 0 now and we can safely assess that we have dropped all unimportant variables from the dataset

Predicting Probability of Customer Churn & Deciding the threshold value

Below I have compared multiple thresholds to determine the optimal p* to reduce error rate in our predictor Side note: Using optimal bayes formula

0.0.2 Conditional Probability (optimal bayes)

Formula: $f(x) = P(Y = 1 \mid X = x)$

[15]:
```
# 1. Predicting the probability of default
# y_prob will be a vector of probabilities that the customer will churn or not␣
↪(1 or 0)
y_prob = logreg2.predict(test2)

# 2. Determining the optimal threshold of the default probability
## The threshold of high churn-risk and low churn-risk will be 0.333
## If p > 1/3, then we consider high churn-risk and should send a promotion to␣
↪the customer or check in with them

# 3. Predicting the label
y_pred = pd.Series([1 if x > 1/3 else 0 for x in y_prob], index=y_prob.index)

# use P = 1/2 as the threshold
y_pred_2 = pd.Series([1 if x > 1/2 else 0 for x in y_prob], index=y_prob.index)
```

P value = 1/3

[16]:
```
# Now we have our probabiltiy of default, I will construct a confusion matrix␣
↪based on decision tree threshold we have computed
# High churn risk > 0.333.
# or high churn risk

y_test = test2['Churn']

cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix : \n", cm)

acc = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
print('Classification Report: ', report)
print('Accuracy: ', acc)
```

```
Confusion Matrix :
 [[1199  350]
 [ 145  416]]
Classification Report:                precision    recall  f1-score   support

           0       0.89      0.77      0.83      1549
           1       0.54      0.74      0.63       561

    accuracy                           0.77      2110
   macro avg       0.72      0.76      0.73      2110
weighted avg       0.80      0.77      0.78      2110

Accuracy:  0.7654028436018957
```

With our threshold at P = 1/2, we can see that recall has increased from ~*77%* -> ~*89%* for predicting churn while f1-score has increased from 83% -> ~86%. So depending on if we care more about correctly identifying true positives or true negatives, vs incorrectly identifying them (false positives/false negatives) then we should use 1/2 as our optimal p-value threshold.

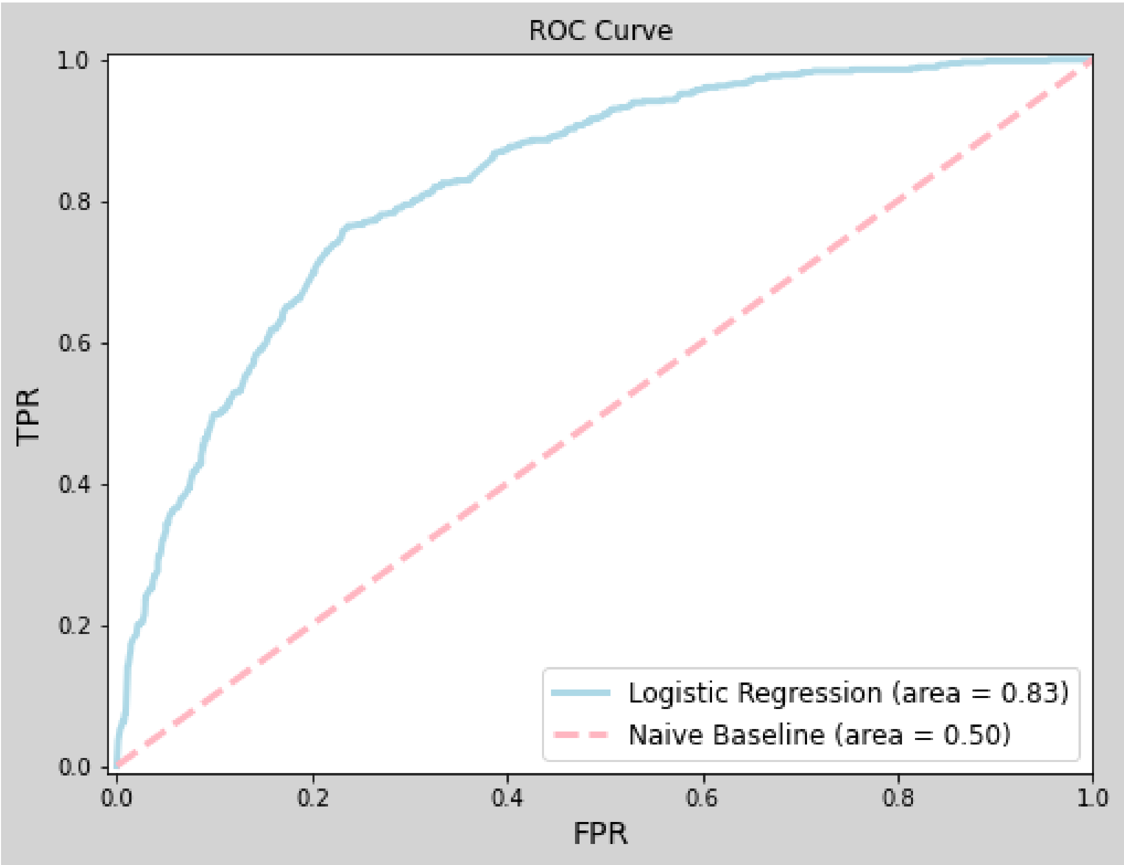
[17]:
```python
# Finding optimial p value threshold for churn prediction
y_test2 = test2['Churn']

cm2 = confusion_matrix(y_test2, y_pred_2)
print("Confusion Matrix : \n", cm2)

acc2 = accuracy_score(y_test2, y_pred_2)
report2 = classification_report(y_test2, y_pred_2)
print('Classification Report: ', report2)
print('Accuracy: ', acc2)
```

```
Confusion Matrix :
 [[1382  167]
 [ 279  282]]
Classification Report:                precision    recall  f1-score   support

           0       0.83      0.89      0.86      1549
           1       0.63      0.50      0.56       561

    accuracy                           0.79      2110
   macro avg       0.73      0.70      0.71      2110
weighted avg       0.78      0.79      0.78      2110

Accuracy:  0.7886255924170616
```

Precision: 83% The ROC curve plots the TPR and FPR for every break-even threshold p between 0.0 and 1.0

[18]:

```
y_train = train2['Churn']
x_train = train2.drop(['Churn'], axis=1)

y_test = test2['Churn']
x_test = test2.drop(['Churn'], axis=1)

fpr, tpr, _ = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6), facecolor='lightgray')
plt.title('ROC Curve', fontsize=12)
plt.xlabel('FPR', fontsize=14)
plt.ylabel('TPR', fontsize=14)
plt.xlim([-0.01, 1.00])
plt.ylim([-0.01, 1.01])
plt.plot(fpr, tpr, lw=3, color = 'lightblue', label='Logistic Regression (area␣
↪= {:0.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], color='lightpink', lw=3, linestyle='--', label='Naive␣
↪Baseline (area = 0.50)')
plt.legend(loc='lower right', fontsize=12)
plt.show()
```



LDA Model

[19]:
```
# First I will change categorical variables to binary variables using OHE

# initialize the OneHotEncoder
drop_enc = OneHotEncoder(drop='first').
↪fit(x_train[['InternetService','Contract']])
print(drop_enc.categories_)
```

```
[array(['DSL', 'Fiber optic', 'No'], dtype=object), array(['Month-to-month',
'One year', 'Two year'], dtype=object)]
```

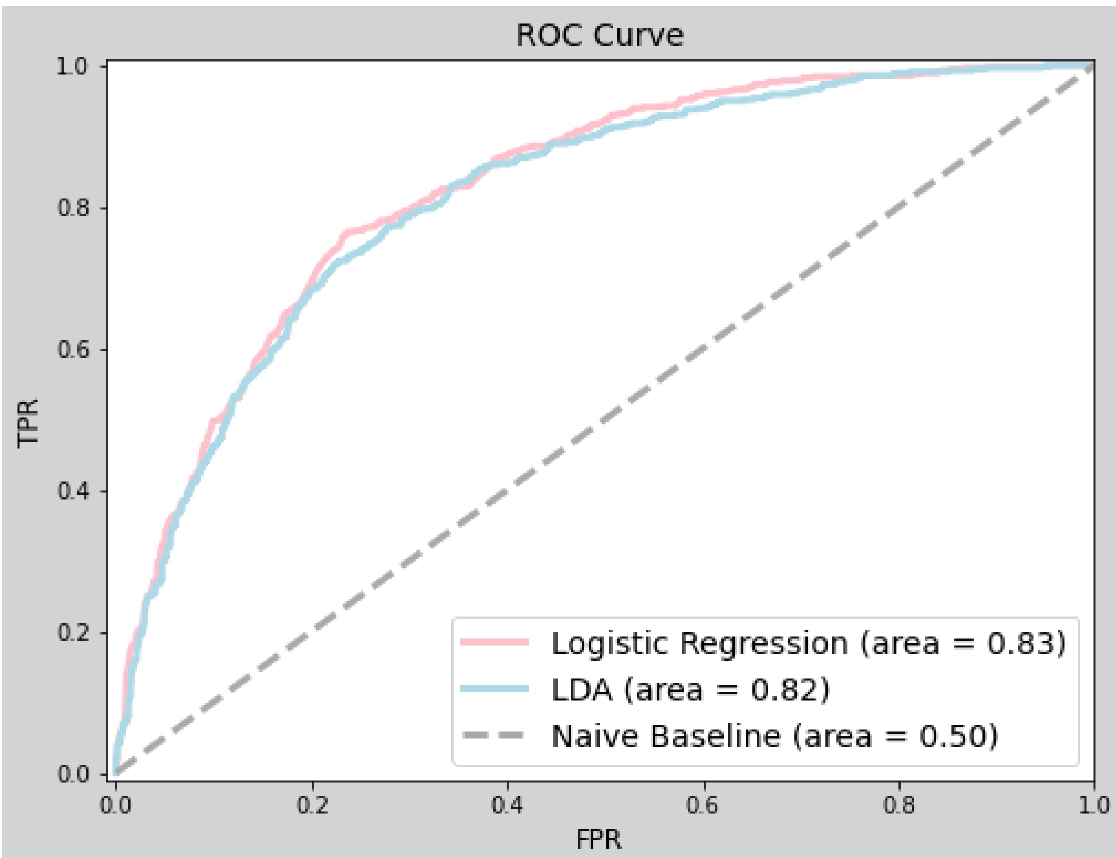
[20]:
```
# Perform the transformation for both the training and the test set.

X_train_categorical = drop_enc.
↪transform(x_train[['InternetService','Contract']]).toarray()
X_train_numerical = x_train[['MonthlyCharges','SeniorCitizen','tenure']].values
# combine the numerical variables and the one-hot encoded categorical variables
X_train_transformed = np.concatenate((X_train_numerical,X_train_categorical),␣
↪axis = 1)

X_test_categorical = drop_enc.transform(x_test[['InternetService','Contract']]).
↪toarray()
X_test_numerical = x_test[['MonthlyCharges','SeniorCitizen','tenure']].values
X_test_transformed = np.concatenate((X_test_numerical,X_test_categorical), axis␣
↪= 1)
```

[21]:
```
lda = LinearDiscriminantAnalysis()
lda.fit(X_train_transformed, y_train)

y_prob_lda = lda.predict_proba(X_test_transformed)
y_pred_lda = pd.Series([1 if x > 1/2 else 0 for x in y_prob_lda[:,1]],␣
↪index=y_prob.index)

cm = confusion_matrix(y_test, y_pred_lda)
print ("Confusion Matrix: \n", cm)
print ("\nAccuracy:", accuracy_score(y_test, y_pred_lda))
```

```
Confusion Matrix:
 [[1365  184]
 [ 268  293]]

Accuracy: 0.785781990521327
```

[22]:
```
fpr_lda, tpr_lda, _ = roc_curve(y_test, y_prob_lda[:,1])
roc_auc_lda = auc(fpr_lda, tpr_lda)
```

```
plt.figure(figsize=(8, 6), facecolor='lightgray')
plt.title('ROC Curve', fontsize=14)
plt.xlabel('FPR', fontsize=12)
plt.ylabel('TPR', fontsize=12)
plt.xlim([-0.01, 1.00])
plt.ylim([-0.01, 1.01])
plt.plot(fpr, tpr, lw=3, color = 'pink', label='Logistic Regression (area = {:0.
 ↪2f})'.format(roc_auc))
plt.plot(fpr_lda, tpr_lda, color = 'lightblue', lw=3, label='LDA (area = {:0.
 ↪2f})'.format(roc_auc_lda))
plt.plot([0, 1], [0, 1], color='darkgray', lw=3, linestyle='--', label='Naive␣
 ↪Baseline (area = 0.50)')
plt.legend(loc='lower right', fontsize=14)
plt.show()
```



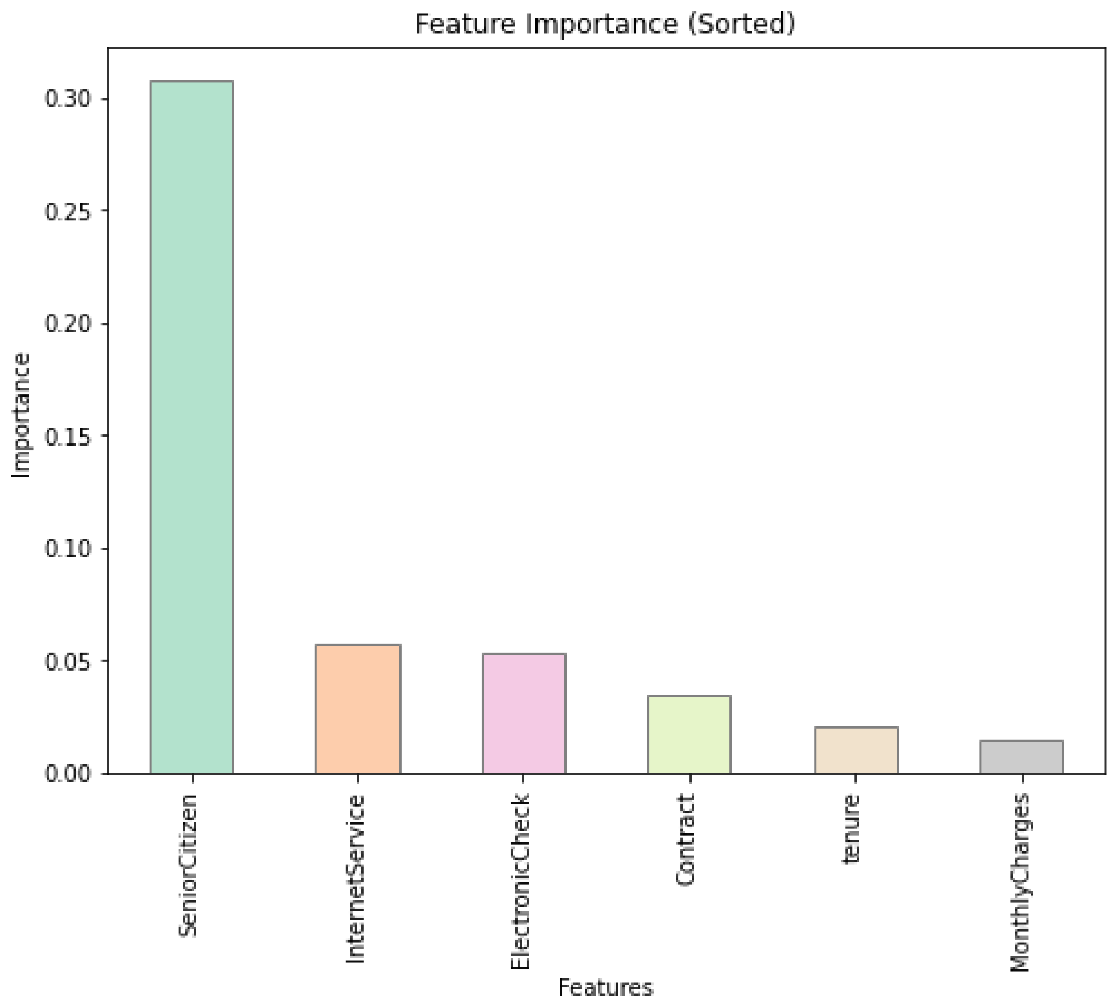
Feature Importance for LDA

[23]:
```
from sklearn.ensemble import RandomForestClassifier
```

```
X_train_df = pd.DataFrame(X_train_transformed, columns=train2.columns)
X_test_df = pd.DataFrame(X_test_transformed, columns=test2.columns)


rf = RandomForestClassifier(n_estimators=200, random_state=42)
rf.fit(X_train_transformed, y_train)
y_pred = rf.predict(X_test_transformed)
score = rf.score(X_test_transformed, y_test)
important_feats = pd.Series(rf.feature_importances_, index=X_train_df.columns).
 ↪sort_values(ascending=False)
print(important_feats)
```

```
Churn               0.513605
SeniorCitizen       0.307479
InternetService     0.056721
ElectronicCheck     0.052663
Contract            0.034173
tenure              0.020344
MonthlyCharges      0.015014
dtype: float64
```

[24]:
```
# Visualizing Feature Importance
importances = rf.feature_importances_
weights = pd.Series(importances, index=X_train_df.columns)
weights = weights.drop(['Churn'])

# Sort the 'weights' Series in ascending order
weights_sorted = weights.sort_values(ascending=False)

# Generate a list of different colors for each bar
num_features = len(weights)
colors = plt.cm.Pastel2(np.linspace(0, 1, num_features))

# Now, create the sorted bar plot using the 'plot()' method and set the 'color'␣
 ↪parameter
weights_sorted.plot(kind='bar', color=colors, edgecolor = 'gray', figsize=(8,␣
 ↪6))

# Optionally, you can add labels and title
plt.xlabel('Features')
plt.ylabel('Importance')
plt.title('Feature Importance (Sorted)')
plt.show()
```



Conclusion & Notes

- With the data that I have available, I have observed that our most important feature to determine churn rate is if the customer is a senior citizen or not (most senior citizens in this dataset churn)
- Lowered variance inflation factors by removing PaymentMethod Credit Card & Payment Method Mailed check for a more a better fit model with p values -> 0
- I minimized the error rate by finding the optimal p value threshold (1/2)
- With more data on the customers, a better accuracy rate and determination of churn rate factors can be determined. For example, if I had access to which platform the customers were using (app, mobile web) or more specifics on the types of services the customer used most, or even if they had dependents then we would be able and built a better model for determining churn

Additional Notes on EDA:

- We can see that monthly charges are not a huge identifier of a customer churning or not - as we have many customers with high monthly charges that have not churned.
- Of the 1,393 customers that churned, 476 of them were senior citizens.
- Of the 1,142 seniors in the dataset, 476 of them churned which is a very high churn rate for senior citizens. (41%)
- Tenure has a negative correlation with churn as we can also see from both the correlation matrix above & our pairplot
- When Tenure is low, and monthly charges are high, we can visually identify a high churn rate

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