Customer Churn Prediction modeling (Kaggle inclass)

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
train = pd.read_csv('C:/Users/jharbour/Desktop/Train_Churn_binary Kaggle.csv')
test = pd.read_csv("C:/Users/jharbour/Desktop/Test_Churn KAggle.csv")
```

In [3]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5282 entries, 0 to 5281
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   gender            5282 non-null   object 
 1   SeniorCitizen     5282 non-null   int64  
 2   Partner           5282 non-null   object 
 3   Dependents        5282 non-null   object 
 4   tenure            5282 non-null   int64  
 5   PhoneService      5282 non-null   object 
 6   MultipleLines     5282 non-null   object 
 7   InternetService   5282 non-null   object 
 8   OnlineSecurity    5282 non-null   object 
 9   OnlineBackup      5282 non-null   object 
 10  DeviceProtection  5282 non-null   object 
 11  TechSupport       5282 non-null   object 
 12  StreamingTV       5282 non-null   object 
 13  StreamingMovies   5282 non-null   object 
 14  Contract          5282 non-null   object 
 15  PaperlessBilling  5282 non-null   object 
 16  PaymentMethod     5282 non-null   object 
 17  MonthlyCharges    5282 non-null   float64
 18  TotalCharges      5282 non-null   object 
 19  Churn             5282 non-null   int64  
dtypes: float64(1), int64(3), object(16)
memory usage: 825.4+ KB
```

In [4]:
```
train.shape,test.shape
```

Out[4]:
```
((5282, 20), (1761, 20))
```

In [5]:
```
# Converting "No internet service" to "No" for the columns listed below
cols = ['OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'OnlineSecurity']

for i in cols:
    train[i] = train[i].replace({"No internet service": "No"})
```

In [6]:
```
# Converting "No phone service" to "No" for the columns listed below
train.MultipleLines = train.MultipleLines.replace({'No phone service':"No"})
```

In [7]:
```
#Addressing numeric features
train.TotalCharges = pd.to_numeric(train.TotalCharges, errors = 'coerce')

train.TotalCharges.fillna(train['TotalCharges'].mean(),inplace=True)

train.TotalCharges.isnull().sum()
```

Out[7]: 0

In [8]:
```
#Idea: Use the average monthly charge most common services, to create new feat
ures
round(train.MonthlyCharges.mean(),2)
```

Out[8]: 64.5

In [9]:
```
train.head(2)
```

Out[9]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetServi
0	Female	0	Yes	Yes	40	No	No	D
1	Male	0	Yes	No	5	Yes	Yes	Fiber op

In [10]:
```
train.shape
```

Out[10]: (5282, 20)

In [11]:
```
month = (train['Contract'] == 'Month-to-month')  & (train.Churn == 1)
train[month]
```

Out[11]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetS
1	Male	0	Yes	No	5	Yes	Yes	Fibe
8	Male	0	No	No	1	Yes	No	Fibe
10	Female	1	No	No	37	Yes	Yes	Fibe
12	Male	0	No	No	2	Yes	No	
13	Female	1	Yes	No	28	Yes	Yes	Fibe
...	...	...	...	...	...	...	...	
5248	Male	1	Yes	No	3	Yes	Yes	Fibe
5261	Male	0	No	No	5	Yes	No	
5265	Male	0	No	No	56	Yes	Yes	Fibe
5270	Female	0	No	No	1	No	No	
5271	Female	0	No	No	1	Yes	No	Fibe

1239 rows × 20 columns

In [12]:
```
len(train[month])
```

Out[12]: 1239

Identifying the percentage of customers with month-to-month contracts that churn

In [13]:
```
(len(train[month])/5282)*100 # the number of churned customers with month-to-m
onth
```

Out[13]: 23.457023854600532

In [14]:
```
# Creating variables and percents representing the percentage of customers lea
ving.

percents = train['Churn'].value_counts(normalize = True ).mul(100).round(2)
#perc_churned = churn_df[churn_df.Churn == "1"].shape[0]
percents
```

Out[14]:
```
0    73.61
1    26.39
Name: Churn, dtype: float64
```

In [15]:
```
# The churn column seems to be standardized since all the descriptive stats ar
e between 0 & 1.
# Now let's look at how many customers are/are not churnning by getting a chur
n count.

counts = train['Churn'].value_counts()


df = pd.DataFrame({'counts': counts, '%':percents})
retained = df['%'][0]
print(retained,'% of customers stayed with the company')

churned = df['%'][1]
print(churned,'% of customers left with the company')
```

```
73.61 % of customers stayed with the company
26.39 % of customers left with the company
```

The majority of churn comes from the month-to-month subgroup of customers. Let's look at their average monthly charges and total charges... maybe we can additionally guage if any delenquincy is present.

In [ ]:
```

```

Data Visualizations to consider

In [16]:
```
import pandas_profiling
pandas_profiling.ProfileReport(train)
```

Overview

Dataset statistics

Number of variables	20
Number of observations	5282
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	11
Duplicate rows (%)	0.2%
Total size in memory	825.4 KiB
Average record size in memory	160.0 B

Variable types

BOOL	13
CAT	4
NUM	3

Warnings

Dataset has 11 (0.2%) duplicate rows	**Duplicates**

Reproduction

Analysis	2021-02-16 01:55:05.431306

Out[16]:

In [17]:
```
train.Contract
```

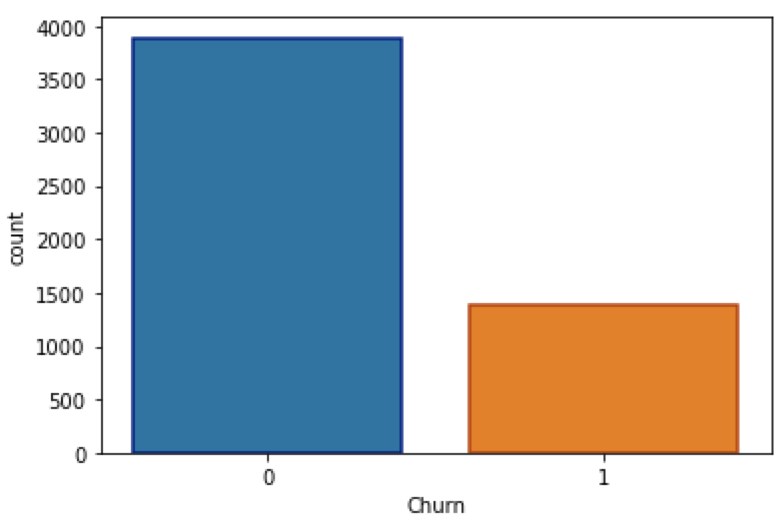
Out[17]:
```
0       Month-to-month
1       Month-to-month
2             One year
3       Month-to-month
4       Month-to-month
             ...
5277    Month-to-month
5278    Month-to-month
5279          Two year
5280          Two year
5281    Month-to-month
Name: Contract, Length: 5282, dtype: object
```

In [18]:
```
train.InternetService
```

Out[18]:
```
0               DSL
1       Fiber optic
2               DSL
3               DSL
4       Fiber optic
           ...
5277            DSL
5278    Fiber optic
5279             No
5280            DSL
5281    Fiber optic
Name: InternetService, Length: 5282, dtype: object
```

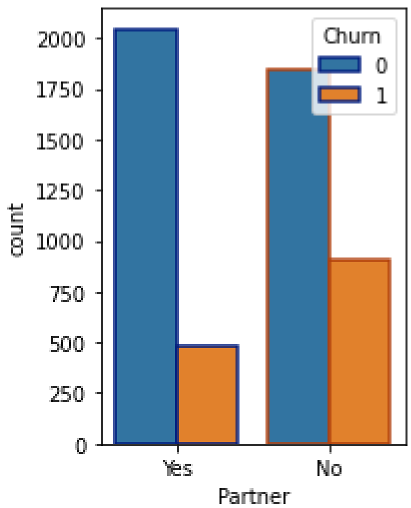
In [19]:
```
# Visual of customer churn
sns.countplot(train['Churn'], edgecolor = sns.color_palette("dark", 2), linewi
dth = 1.5)
```

Out[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1dfae8f9070>
```



In [20]:
```
# plot the sub categories of the train data

plt.subplot(1,2,1)
sns.countplot('Partner', hue = 'Churn', data = train, edgecolor = sns.color_pa
lette("dark", 2), linewidth = 1.5)
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x1dfaeac0490>

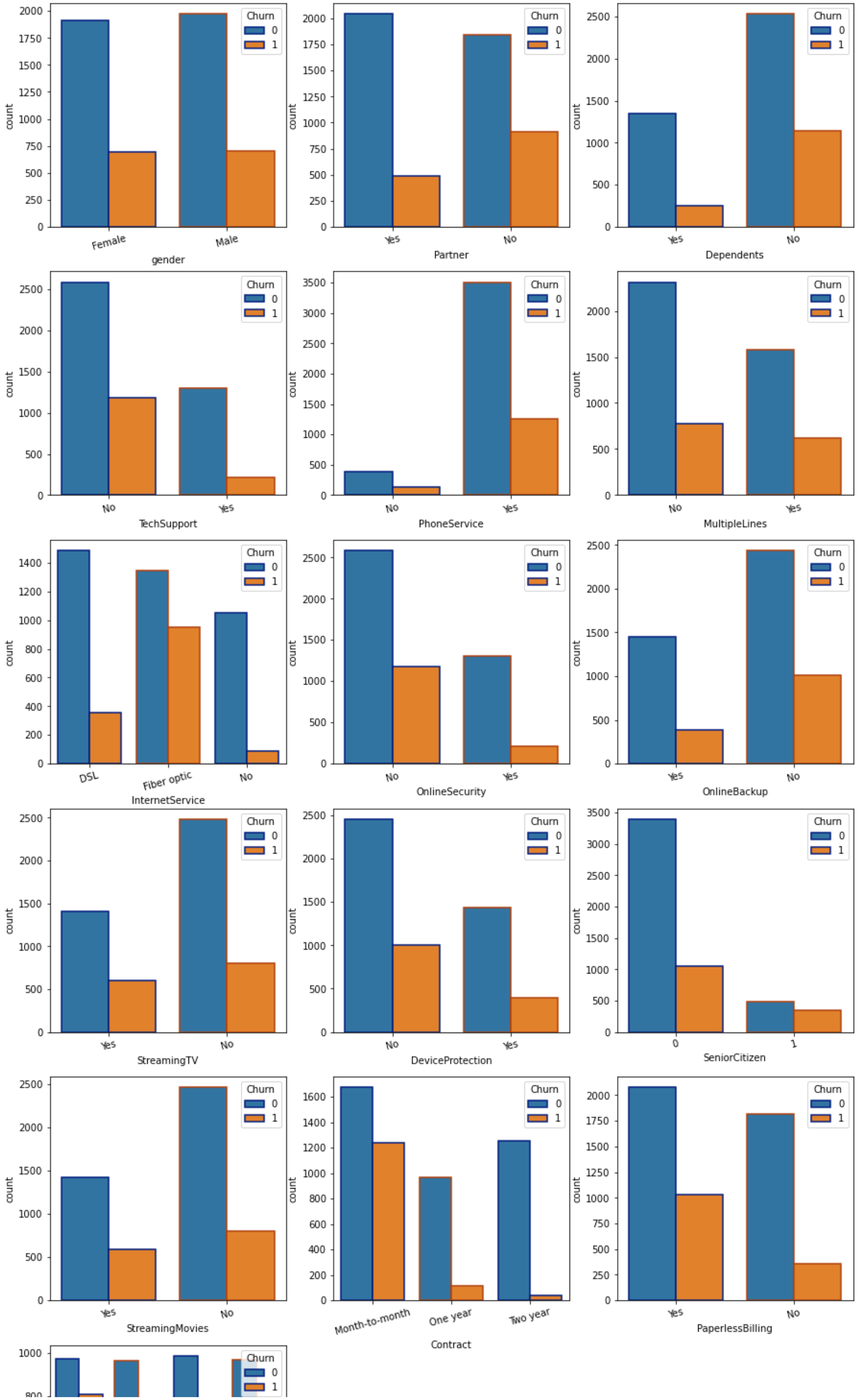


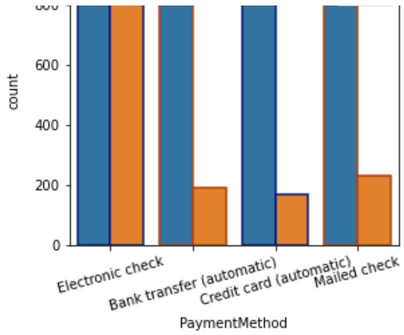
In [21]:
```
cat_feats = ['gender', 'Partner', 'Dependents', 'TechSupport',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
       'OnlineBackup', 'StreamingTV','DeviceProtection','SeniorCitizen',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod']
```

In [22]:
```
list(enumerate(cat_feats))
```

Out[22]:
```
[(0, 'gender'),
 (1, 'Partner'),
 (2, 'Dependents'),
 (3, 'TechSupport'),
 (4, 'PhoneService'),
 (5, 'MultipleLines'),
 (6, 'InternetService'),
 (7, 'OnlineSecurity'),
 (8, 'OnlineBackup'),
 (9, 'StreamingTV'),
 (10, 'DeviceProtection'),
 (11, 'SeniorCitizen'),
 (12, 'StreamingMovies'),
 (13, 'Contract'),
 (14, 'PaperlessBilling'),
 (15, 'PaymentMethod')]
```

In [23]:
```
plt.figure(figsize = (15,30))
for i in enumerate(cat_feats):
    plt.subplot(6,3,i[0]+1)
    sns.countplot(i[1], hue = 'Churn', data = train, edgecolor = sns.color_pal
ette("dark", 2), linewidth = 1.5)
    plt.xticks(rotation = 15)
```


Churn
0
1
count
Female
Male
gender
Yes
No
Partner
Dependents
TechSupport
PhoneService
MultipleLines
DSL
Fiber optic
InternetService
OnlineSecurity
OnlineBackup
StreamingTV
DeviceProtection
SeniorCitizen
StreamingMovies
Month-to-month
One year
Two year
Contract
PaperlessBilling



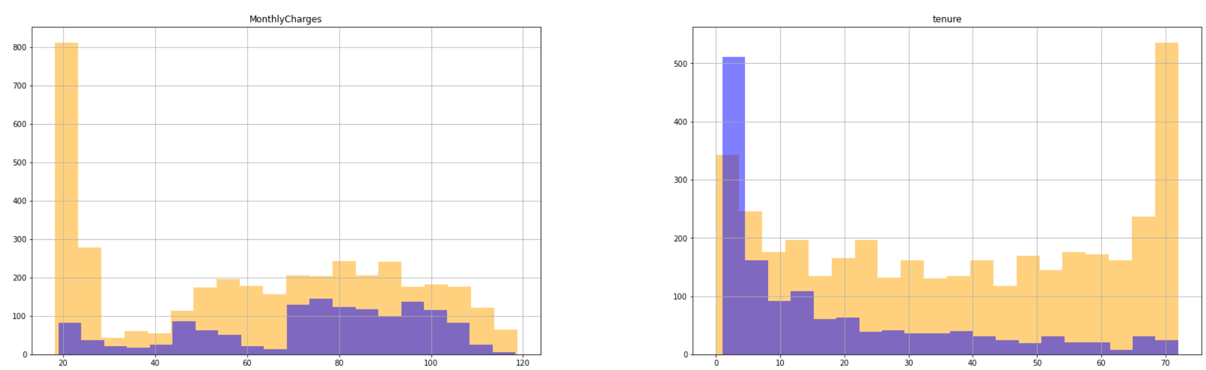
In [ ]:

Looking at numerical variables

In [24]:
```
train['Churn2']= train['Churn'].astype(str)
train['Churn2'].replace(["0","1"],["No","Yes"], inplace = True)
```

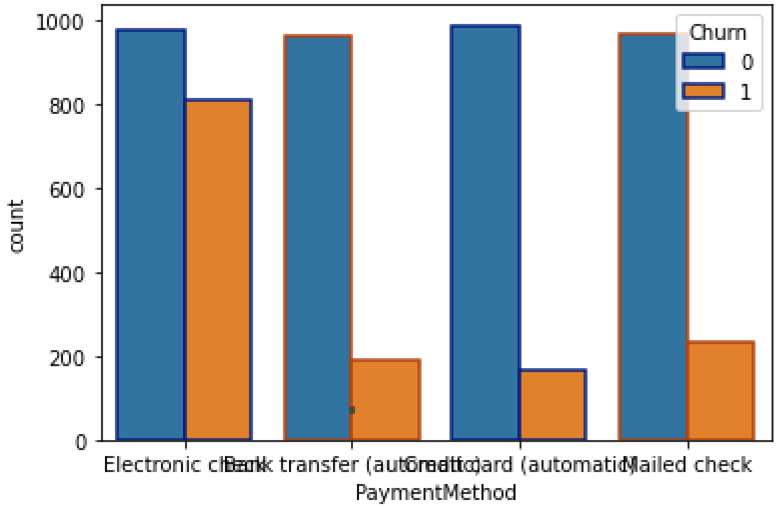
In [25]:
```
num_feats = ['tenure','MonthlyCharges']
fig, ax = plt.subplots(1, 2, figsize = (28,8))

train[train.Churn2 == 'No'][num_feats].hist(bins=20,color = 'orange', alpha = 0.5, ax = ax)
train[train.Churn2 == 'Yes'][num_feats].hist(bins=20,color = 'blue', alpha = 0.5, ax = ax)
```

Out[25]:
```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x000001DFAEE773A0>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x000001DFAEAAAE50>],
      dtype=object)
```



In [26]:
```
sns.barplot(x='Churn', y = 'MonthlyCharges', data = train)
sns.countplot(i[1], hue = 'Churn', data = train, edgecolor = sns.color_palette
("dark", 2), linewidth = 1.5)
```

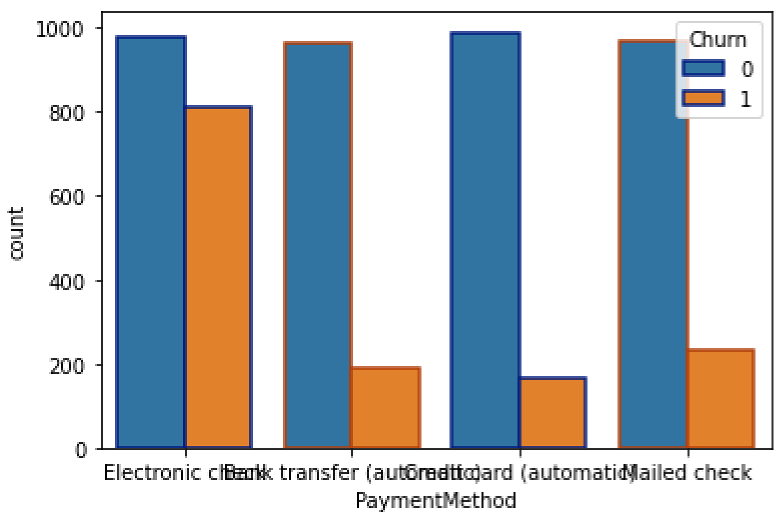
Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x1dfb02cb940>



In [ ]:

In [27]:
```
sns.barplot(x='Churn', y = 'tenure', data = train)
sns.countplot(i[1], hue = 'Churn', data = train, edgecolor = sns.color_palette
("dark", 2), linewidth = 1.5)
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x1dfb030ae20>



In [28]:
```
#graph1 = sns.FacetGrid(train,col='TotalCharges', hue ="Churn", height =4, asp
ect=1)
#graph1.map(plt.scatter,"gender", "SeniorCitizen")
```

In [ ]:

'Monthly Charges' shows most of the retained customers have monthly bills between roughly 20 - 30 dollars with the highest churn between 70 - 100 dollars. Secondly, 'tenure' suggests most churn occurs within the first 10 months of service.

In [29]:
```
#Use the average monthly charge most common services, to create a basic packag
e offered clser to $3o

round(train.MonthlyCharges.mean(),2)
```

Out[29]: 64.5

In [30]:
```
# Tenure and TotalCharges are two features that drive customer churn as well a
s SeniorCitizenship
# ... Let's look at age to produce service packages
train.corr()
```

Out[30]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	Churn
SeniorCitizen	1.000000	0.016098	0.216524	0.101319	0.145914
tenure	0.016098	1.000000	0.246406	0.825827	-0.361497
MonthlyCharges	0.216524	0.246406	1.000000	0.647774	0.180156
TotalCharges	0.101319	0.825827	0.647774	1.000000	-0.213306
Churn	0.145914	-0.361497	0.180156	-0.213306	1.000000

In [ ]:

In [31]:
```
mon_tot_chrg = (train['Contract'] == 'Month-to-month')  & (train.Churn == 1) &
(train.TotalCharges)
train[mon_tot_chrg].describe()
```

Out[31]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	Churn
count	1239.000000	1239.000000	1239.000000	1239.000000	1239.0
mean	0.258273	13.378531	72.253269	1096.634463	1.0
std	0.437862	15.229199	24.093061	1410.682621	0.0
min	0.000000	1.000000	18.950000	19.100000	1.0
25%	0.000000	2.000000	54.200000	94.575000	1.0
50%	0.000000	7.000000	77.500000	503.600000	1.0
75%	1.000000	19.000000	90.725000	1472.850000	1.0
max	1.000000	71.000000	114.500000	7548.100000	1.0

In [ ]:

In [32]:
```
# Tenure MonthlyCharges, and TotalCharges are features that seem to drive cust
omer churn
# ... Let's look at age to produce new features... looking at correlation
train.corr()
```

Out[32]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	Churn
SeniorCitizen	1.000000	0.016098	0.216524	0.101319	0.145914
tenure	0.016098	1.000000	0.246406	0.825827	-0.361497
MonthlyCharges	0.216524	0.246406	1.000000	0.647774	0.180156
TotalCharges	0.101319	0.825827	0.647774	1.000000	-0.213306
Churn	0.145914	-0.361497	0.180156	-0.213306	1.000000

In [ ]:

In [33]:
```
train = pd.get_dummies(train, columns = ['gender', 'Partner', 'Dependents', 'T
echSupport',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
       'OnlineBackup', 'StreamingTV','DeviceProtection','SeniorCitizen',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod'], dr
op_first = True)
```

In [34]:
```
train.head()
```

Out[34]:

	tenure	MonthlyCharges	TotalCharges	Churn	Churn2	gender_Male	Partner_Yes	Dependents
0	40	50.85	2036.55	0	No	0	1	
1	5	81.30	416.30	1	Yes	1	1	
2	63	71.50	4576.30	0	No	1	0	
3	36	34.85	1267.20	0	No	0	0	
4	60	74.35	4453.30	0	No	1	1	

5 rows × 25 columns

In [35]:
```
train.shape
```

Out[35]: (5282, 25)

In [36]:
```
from sklearn.preprocessing import StandardScaler

#Performing feature scaling on 'tenure','MonthlyCharges','TotalCharges' to bri
ng them on the same scale
sc = StandardScaler()
cols_for_scaling = ['tenure','MonthlyCharges','TotalCharges']

# Apllying feature scaling on the three columns selected above with fit_transf
orm ()
train[cols_for_scaling] = sc.fit_transform(train[cols_for_scaling])
```

In [37]:
```
train.head(2)
```

Out[37]:

	tenure	MonthlyCharges	TotalCharges	Churn	Churn2	gender_Male	Partner_Yes	Depende
0	0.320194	-0.455657	-0.097980	0	No	0	1	
1	-1.105281	0.560476	-0.816328	1	Yes	1	1	

2 rows × 25 columns

Test.csv Transformations (the same as with training set)

In [38]:
```
test.shape
```

Out[38]: (1761, 20)

In [39]:
```
# Saving the Customer number for later use
cust_num = test['Customer Number']

custnumbr = pd.DataFrame(cust_num)
custnumbr.columns = ['Customer Number']
custnumbr.head(2)
```

Out[39]:

	Customer Number
0	4709-LKHYG
1	8999-XXGNS

In [40]:
```
custnumbr.to_csv('custnumbr.csv')
```

In [41]:
```
#Removing the Customer Number from the test set.

test = test.drop(['Customer Number'], axis =1)
```

In [42]:
```
test.head(2)
```

Out[42]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetServi
0	Female	0	Yes	Yes	29	Yes	No	
1	Female	1	Yes	No	72	Yes	Yes	Fiber op

In [43]:
```
# Converting "No internet service" to "No" for the columns listed below
cols = ['OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'OnlineSecurity']

for i in cols:
    test[i] = test[i].replace({"No internet service": "No"})

test.MultipleLines = test.MultipleLines.replace({'No phone service':"No"})
```

In [44]:
```
test.head(2)
```

Out[44]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetServi
0	Female	0	Yes	Yes	29	Yes	No	
1	Female	1	Yes	No	72	Yes	Yes	Fiber op

In [45]:
```
test.TotalCharges = pd.to_numeric(test.TotalCharges, errors = 'coerce')

test.TotalCharges.fillna(test['TotalCharges'].mean(),inplace=True)

test.TotalCharges.isnull().sum()
```

Out[45]: 0

In [46]:
```
# Performing One Hot Encoding via the get_dummies method

test = pd.get_dummies(test, columns = ['gender', 'SeniorCitizen', 'Partner',
'Dependents',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
       'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod'], dr
op_first = True)
```

In [47]:
```
test.head(2)
```

Out[47]:

	tenure	MonthlyCharges	TotalCharges	gender_Male	SeniorCitizen_1	Partner_Yes	Dependent
0	29	20.00	540.05	0	0	1	
1	72	105.75	7629.85	0	1	1	

2 rows × 23 columns

In [48]:
```
test.shape
```

Out[48]: (1761, 23)

In [49]:
```
from sklearn.preprocessing import StandardScaler

#Performing feature scaling on 'tenure','MonthlyCharges','TotalCharges' to bri
ng them on the same scale
sc = StandardScaler()
cols_for_scaling = ['tenure','MonthlyCharges','TotalCharges']

# Apllying feature scaling on the three columns selected above with fit_transf
orm ()
test[cols_for_scaling] = sc.fit_transform(test[cols_for_scaling])
```

In [50]:
```
test.head()
```

Out[50]:

	tenure	MonthlyCharges	TotalCharges	gender_Male	SeniorCitizen_1	Partner_Yes	Depend
0	-0.165723	-1.496029	-0.794724	0	0	1	
1	1.585229	1.321353	2.300152	0	1	1	
2	0.526514	0.003837	0.299688	1	0	1	
3	-0.287883	-1.515742	-0.801054	1	0	0	
4	-1.305878	-1.308751	-1.019251	0	1	0	

5 rows × 23 columns

In [ ]:
```

```

Feature selection

In [51]:
```
X = train.drop(['Churn','Churn2'], axis = 1)
y = train['Churn']
```

In [52]:
```
X.shape
```

Out[52]:
```
(5282, 23)
```

Extracting important features using ExtraTreesRegressor

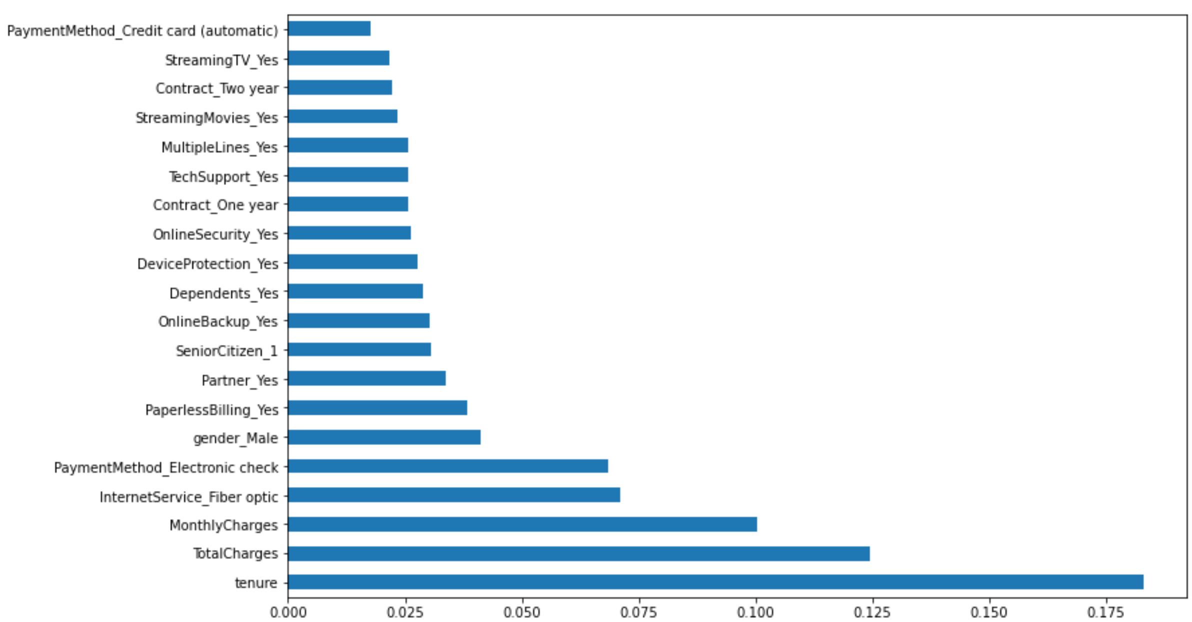
In [53]:
```
from sklearn.ensemble import ExtraTreesRegressor

selection = ExtraTreesRegressor()
selection.fit(X,y)
```

Out[53]:
```
ExtraTreesRegressor()
```

In [54]:
```
print(selection.feature_importances_)
```

```
[0.18304609 0.10047371 0.12438881 0.04126082 0.03382654 0.02876172
 0.02573611 0.01031563 0.02564415 0.0709551  0.00891894 0.02623711
 0.0302782  0.02161667 0.02777995 0.03071026 0.02341739 0.02581619
 0.02225685 0.03823203 0.01766738 0.06855037 0.01410996]
```

In [55]:
```
#Plotting a graph that shows the most important features based on correlation
 to Churn

plt.figure(figsize = (12,8))
feat_importances = pd.Series(selection.feature_importances_, index = X.columns
)
feat_importances.nlargest(20).plot(kind='barh')
plt.show()
```



Fitting model using LogisticRegression

In [56]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.334,shuffle =True, stratify = y,random_state =None)
```

In [57]:
```
# Logistic Regression model
from sklearn.linear_model import LogisticRegressionCV
```

In [58]:
```
logmodel = LogisticRegressionCV(Cs = 100, cv =10,penalty= 'l2', solver = 'lbfgs', max_iter= 500)
logmodel.fit(X_train, y_train)
```

Out[58]:
```
LogisticRegressionCV(Cs=100, cv=10, max_iter=500)
```

In [59]:
```
LRpred = logmodel.predict(X_test)
```

In [60]:
```
logmodel.score(X_train,y_train)
```

Out[60]:
```
0.8126243957918681
```

In [61]:
```
logmodel.score(X_test,y_test)
```

Out[61]:
```
0.796600566572238
```

In [62]:
```
preds = test
```

In [63]:
```
preds.shape
```

Out[63]:
```
(1761, 23)
```

In [64]:
```
logmodel.predict_proba(preds)
```

Out[64]:
```
array([[0.95729751, 0.04270249],
       [0.8966189 , 0.1033811 ],
       [0.97550964, 0.02449036],
       ...,
       [0.41268282, 0.58731718],
       [0.76972744, 0.23027256],
       [0.50030656, 0.49969344]])
```

In [65]:
```
from sklearn import metrics
print(metrics.accuracy_score(y_test ,LRpred))
```

```
0.796600566572238
```

In [66]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test, LRpred)
```

Out[66]:
```
array([[1169,  130],
       [ 229,  237]], dtype=int64)
```

In [67]:
```
from sklearn.metrics import classification_report

print(classification_report(y_test, LRpred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.90      0.87      1299
           1       0.65      0.51      0.57       466

    accuracy                           0.80      1765
   macro avg       0.74      0.70      0.72      1765
weighted avg       0.79      0.80      0.79      1765
```

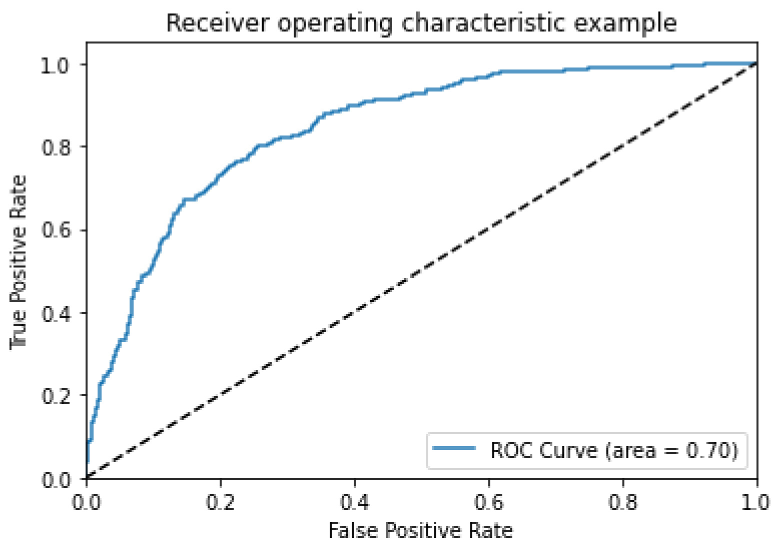
In [68]:
```
from sklearn.metrics import roc_auc_score
```

In [69]:
```
logit_roc_auc = roc_auc_score(y_test , logmodel.predict(X_test))
print ("Logistic AUC = %2.2f" % logit_roc_auc)
print (classification_report(y_test, logmodel.predict(X_test)))
```

```
Logistic AUC = 0.70
              precision    recall  f1-score   support

           0       0.84      0.90      0.87      1299
           1       0.65      0.51      0.57       466

    accuracy                           0.80      1765
   macro avg       0.74      0.70      0.72      1765
weighted avg       0.79      0.80      0.79      1765
```

In [70]:
```
from sklearn.metrics import roc_curve , auc
fpr, tpr, thresholds = roc_curve(y_test, logmodel.predict_proba(X_test)[:,1])
```

In [71]:
```
plt.figure()
plt.plot(fpr,tpr, label= 'ROC Curve (area = %0.2f)' % logit_roc_auc)
plt.plot([0,1],[0,1], 'k--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc = 'lower right')
plt.show()
```



In [72]:
```
#LRpred3 = logmodel.predict_proba(preds)
#LRpred3
```

In [73]:
```
#LRresults3 = pd.DataFrame(LRpred3)
```

In [74]:
```
#LRresults3.to_csv('LRresults3.csv')
```

In [75]:
```
#LogisticRegressionCV()
```

Tuning the Model via GridSearchCV

In [76]:
```
from sklearn.model_selection import GridSearchCV

params = [{'Cs':[1,10,100,1000], 'solver':['liblinear','lbfgs'],
          'tol':[0.0001,0.001,0.01,0.1]}]

grid_search = GridSearchCV(estimator = logmodel,
                           param_grid = params,
                           scoring = 'accuracy',
                             cv = 10,
                              n_jobs = -1)
grid_search = grid_search.fit(X_train,y_train)
```

In [77]:
```
#LogisticRegressionCV()
```

Out[77]:
```
LogisticRegressionCV()
```

In [78]:
```
logmod_accuracy = grid_search.best_score_
logmod_accuracy
```

Out[78]:
```
0.81004921004921
```

In [79]:
```
grid_search.best_params_
```

Out[79]:
```
{'Cs': 100, 'solver': 'liblinear', 'tol': 0.001}
```

In [110]:
```
# Modifiying the suggested parameters

logmodel = LogisticRegressionCV(Cs = 100, cv =10,penalty= 'l2', solver = 'lbfgs', tol= 0.001, max_iter= 500)
logmodel.fit(X_train, y_train)
```

Out[110]:
```
LogisticRegressionCV(Cs=100, cv=10, max_iter=500, tol=0.001)
```

In [111]:
```
LRpred = logmodel.predict(X_test)
```

In [112]:
```
logmodel.score(X_train,y_train)
```

Out[112]:
```
0.8126243957918681
```

In [113]:
```
logmodel.score(X_test,y_test)
```

Out[113]:
```
0.796600566572238
```

In [109]:
```
logit_roc_auc = roc_auc_score(y_test , logmodel.predict(X_test))
print ("Logistic AUC = %2.2f" % logit_roc_auc)
print (classification_report(y_test, logmodel.predict(X_test)))
```

```
Logistic AUC = 0.70
              precision    recall  f1-score   support

           0       0.84      0.90      0.87      1299
           1       0.65      0.51      0.57       466

    accuracy                           0.80      1765
   macro avg       0.74      0.70      0.72      1765
weighted avg       0.79      0.80      0.79      1765
```

In [ ]:
```

```

In [84]:
```
#preds.shape
```

In [85]:
```
#LRaccuracy = round(metrics.accuracy_score(y_test, LRpred)*100, 2)
#LRaccuracy
```

In [86]:
```
#LRpred2 = logmodel.predict_proba(X_test)
#LRpred2
```

In [87]:
```
#LRresults= pd.DataFrame(LRpred2)
```

In [88]:
```
#LRresults.to_csv('LRresults.csv')
```

In [89]:
```
#test.head()
```

RandomForest model for comparison

In [90]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [91]:
```
Rfmodel = RandomForestClassifier( n_estimators = 70, criterion = 'entropy', ma
x_depth = 10, min_samples_split = 6 )
```

In [92]:
```
Rfmodel.fit(X_train,y_train)
```

Out[92]:
```
RandomForestClassifier(criterion='entropy', max_depth=10, min_samples_split=
6,
                       n_estimators=70)
```

In [93]:
```
from sklearn.model_selection import GridSearchCV
```

In [94]:
```
#from sklearn.model_selection import GridSearchCV

parameters = {'n_estimators' : (10,30,50,70,90,100),
                'criterion'  : ('gini','entropy') ,
                'max_depth'  : (3,5,7,9,10) ,
                 'max_features' : ('auto','sqrt'),
                 'min_samples_split' : (2,4,6)}
```

In [95]:
```
Rf_grid = GridSearchCV(RandomForestClassifier(n_jobs = -1, oob_score = False),
param_grid = parameters, cv = 3, verbose = True)
```

In [96]:
```
Rf_grid_mod = Rf_grid.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 360 candidates, totalling 1080 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent worke
rs.
[Parallel(n_jobs=1)]: Done 1080 out of 1080 | elapsed:  2.0min finished
```

In [97]:
```
Rf_grid_mod.best_estimator_
```

Out[97]:
```
RandomForestClassifier(max_depth=7, min_samples_split=4, n_estimators=70,
                       n_jobs=-1)
```

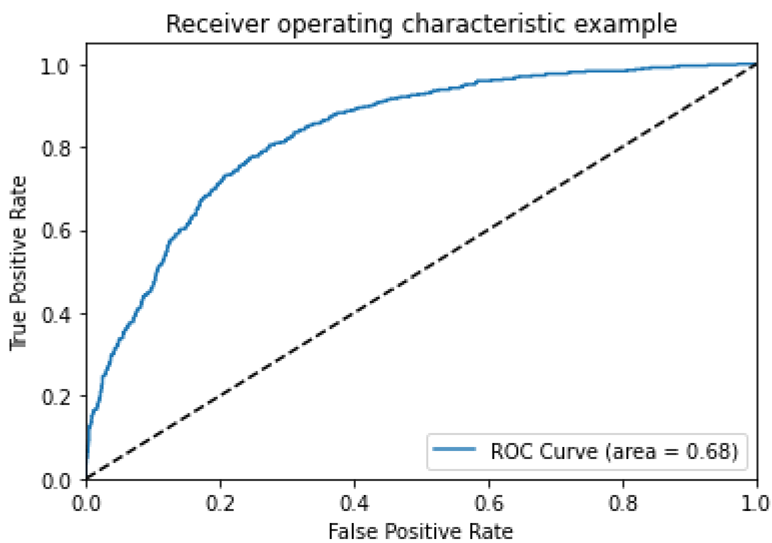
In [98]:
```
Rf_grid_mod.best_score_
```

Out[98]: 0.8160311114602639

In [114]:
```
logit_roc_auc = roc_auc_score(y_test , Rfmodel.predict(X_test))
print ("Logistic AUC = %2.2f" % logit_roc_auc)
print (classification_report(y_test, Rfmodel.predict(X_test)))
```

```
Logistic AUC = 0.68
              precision    recall  f1-score   support

           0       0.82      0.90      0.86      1299
           1       0.63      0.45      0.53       466

    accuracy                           0.78      1765
   macro avg       0.72      0.68      0.69      1765
weighted avg       0.77      0.78      0.77      1765
```

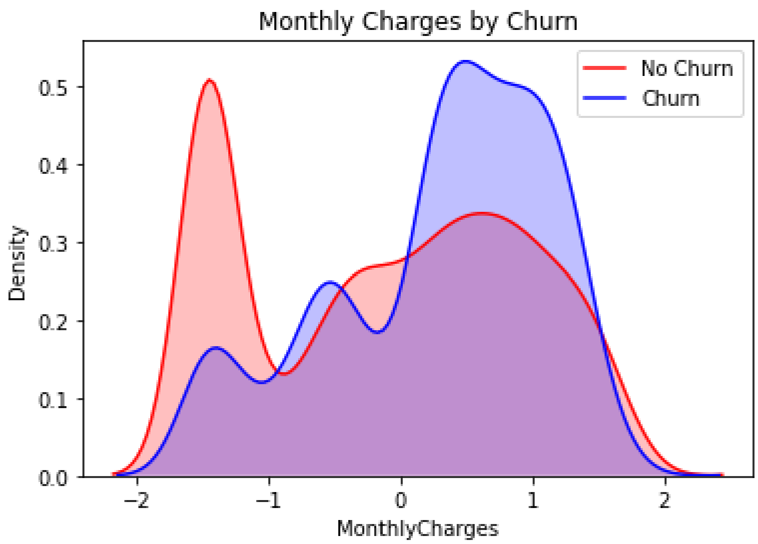
In [115]:
```
from sklearn.metrics import roc_curve , auc
fpr, tpr, thresholds = roc_curve(y_test, Rfmodel.predict_proba(X_test)[:,1])

plt.figure()
plt.plot(fpr,tpr, label= 'ROC Curve (area = %0.2f)' % logit_roc_auc)
plt.plot([0,1],[0,1], 'k--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc = 'lower right')
plt.show()
```



Most important Visuals - combining features to see how they interact to impact Churn.

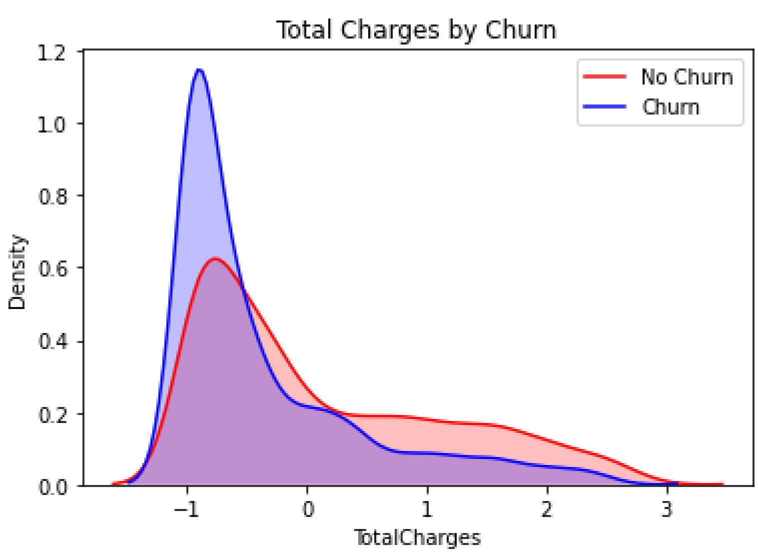
In [99]:
```
monthlycharges = sns.kdeplot(train.MonthlyCharges[(train['Churn']==0) ],
                             color = "Red", shade = True)
monthlycharges = sns.kdeplot(train.MonthlyCharges[(train['Churn']==1)],
                             ax=monthlycharges, color = "Blue", shade = True)
monthlycharges.legend(['No Churn','Churn'],loc = 'upper right')
monthlycharges.set_ylabel('Density')
monthlycharges.set_xlabel('MonthlyCharges')
monthlycharges.set_title('Monthly Charges by Churn')
```

Out[99]: Text(0.5, 1.0, 'Monthly Charges by Churn')



In [100]:
```
totalcharges = sns.kdeplot(train.TotalCharges[(train['Churn']==0) ],
                             color = "Red", shade = True)
totalcharges = sns.kdeplot(train.TotalCharges[(train['Churn']==1)],
                             ax=totalcharges, color = "Blue", shade = True)
totalcharges.legend(['No Churn','Churn'],loc = 'upper right')
totalcharges.set_ylabel('Density')
totalcharges.set_xlabel('TotalCharges')
totalcharges.set_title('Total Charges by Churn')
```

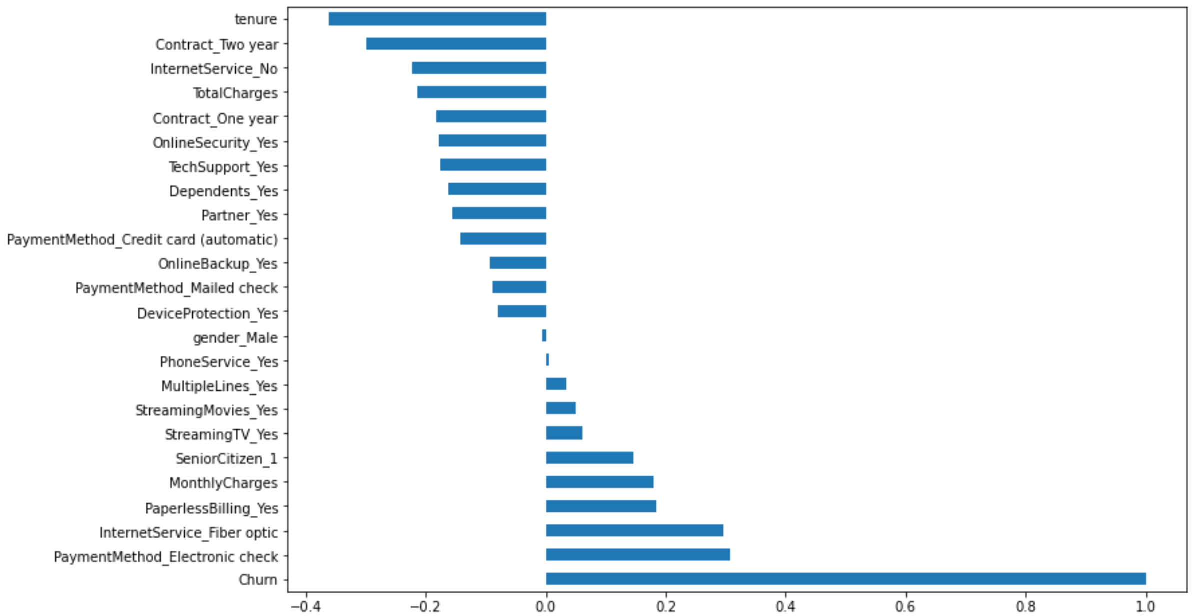
Out[100]: Text(0.5, 1.0, 'Total Charges by Churn')



Insight : Churn is high when monthly charges are high

In [101]:
```
plt.figure(figsize = (12,8))
train.corr()['Churn'].sort_values(ascending = False).plot(kind = 'barh')
```

Out[101]: <matplotlib.axes._subplots.AxesSubplot at 0x1dfae6bd1f0>



In [ ]:

Project Findings and Overview:

The customer churn rate present in this company is slightly higher than the national average but is not too far from the norm. If attention is given to monthly contracts, charges for services, and , obviously, increasing tenure, this company can make many gains towards more profits. Upon further investigation I found that the majority of the 26% churned comes from customers with month-to-month contracts (23.46% to be exact).

Logistic Regression fared well when compared to a Random Forest likely due to its universal innate robustness as a classifier. The models respectively achieved accuracies of 81.2% and 81.6% once optimization via SeachGridCV had been employed. Once deployed into Kaggle and scored, accuracy improved to 83.4%. However, the Random Forest produce a lower AUC which is a more complete metric.

In [ ]: