Telco Customer Churn

Context:

"Predict behavior to retain customers. You can analyze all relevant customer data and develop focused customer retention programs."

Content:

Each row represents a customer, each column contains customer's attributes described on the column Metadata.

The raw data contains 7043 rows (customers) and 21 columns (features).

The "Churn" column is our target.

Metadata

- customerID : Customer ID
- gender: Whether the customer is a male or a female
- SeniorCitizen: Whether the customer is a senior citizen or not (1, 0)
- Partner: Whether the customer has a partner or not (Yes, No)
- Dependents: Whether the customer has dependents or not (Yes, No)
- tenure: Number of months the customer has stayed with the company
- PhoneService: Whether the customer has a phone service or not (Yes, No)
- MultipleLines: Whether the customer has multiple lines or not (Yes, No, No phone service)
- InternetService: Customer's internet service provider (DSL, Fiber optic, No)
- OnlineSecurity: Whether the customer has online security or not (Yes, No, No internet service)
- OnlineBackup: Whether the customer has online backup or not (Yes, No, No internet service)
- DeviceProtection: Whether the customer has device protection or not (Yes, No, No internet service)
- TechSupport: Whether the customer has tech support or not (Yes, No, No internet service)
- StreamingTV: Whether the customer has streaming TV or not (Yes, No, No internet service)
- StreamingMovies: Whether the customer has streaming movies or not (Yes, No, No internet service)
- Contract: The contract term of the customer (Month-to-month, One year, Two year)
- PaperlessBilling: Whether the customer has paperless billing or not (Yes, No)
- PaymentMethod: The customer's payment method (Electronic check, Mailed check, Bank transfer (automatic), Credit card (automatic))
- MonthlyCharges: The amount charged to the customer monthly
- TotalCharges: The total amount charged to the customer
- Churn: Whether the customer churned or not (Yes or No)

Data Loading

In [60]:
```
#Importing libraries
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
from PIL import  Image
%matplotlib inline
import pandas as pd
import seaborn as sns
import itertools
import warnings
warnings.filterwarnings("ignore")
import io
import plotly.offline as py#visualization
py.init_notebook_mode(connected=True)#visualization
import plotly.graph_objs as go#visualization
import plotly.tools as tls#visualization
import plotly.figure_factory as ff#visualization
```

In [61]:
```
telcom = pd.read_csv('Downloads/Telco-Customer-Churn.csv')
```

In [62]:
```
print('The Shape of the Dataset is ',telcom.shape)
print('\n The Columns of the Dataset : ',telcom.columns)
```

```
The Shape of the Dataset is  (7043, 21)

 The Columns of the Dataset :  Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [63]:
```
telcom.head(5)
```

Out[63]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupp
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	Yes	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	Yes	
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	No	

5 rows × 21 columns

Data Cleaning

In [64]:
```
telcom = telcom[telcom.TotalCharges != " "]
telcom["TotalCharges"] = telcom["TotalCharges"].astype(float)

for i in [ 'MultipleLines','OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
                'TechSupport','StreamingTV', 'StreamingMovies'] :
    telcom[i]  = telcom[i].replace({'No internet service' : 'No'})
```

Exploratory Data Analysis

We now check the balance of the response variable i.e Churn :

In [65]:
```
telcom.Churn.value_counts()
```

Out[65]:
```
No     5163
Yes    1869
Name: Churn, dtype: int64
```

We do have more categorical features as compared to continuous features. We take a look at the various categories in each feature.

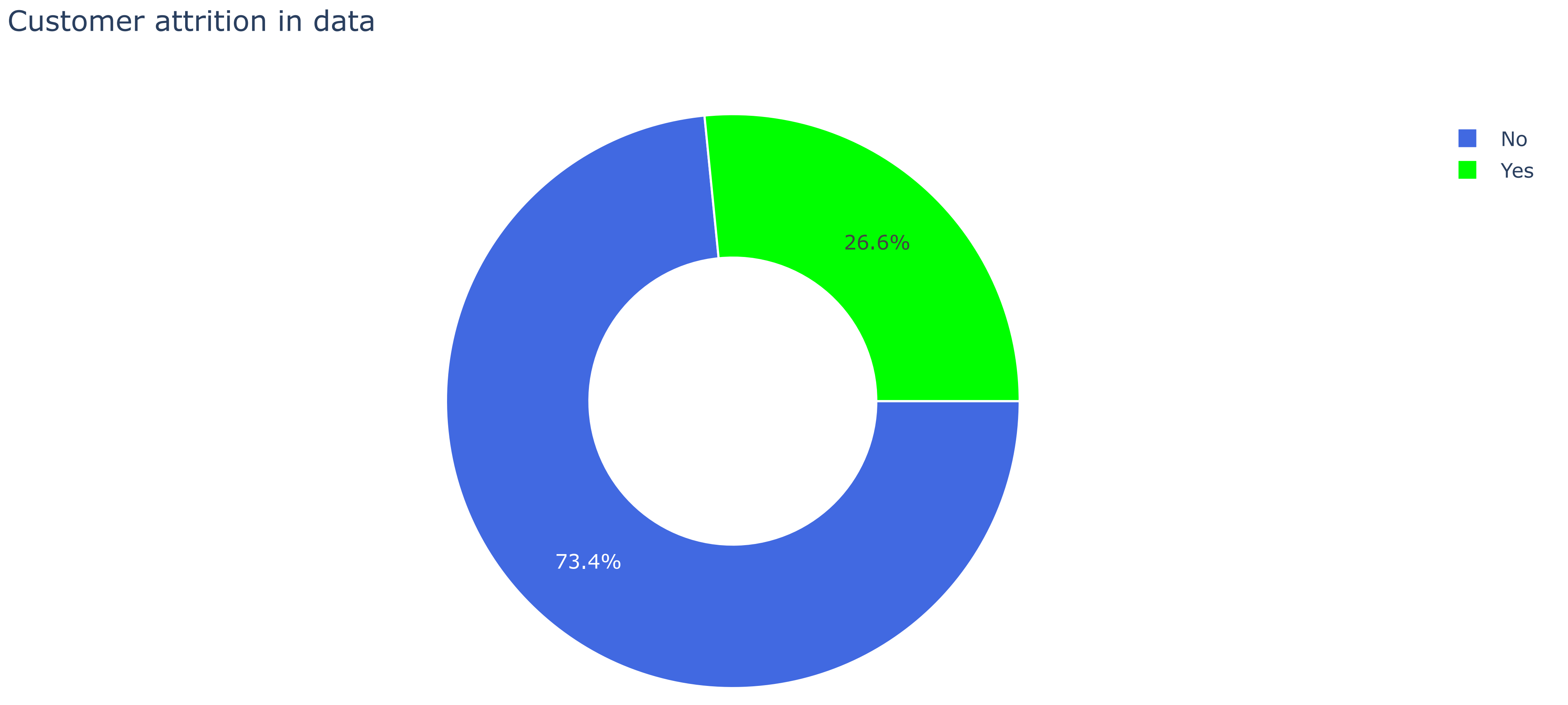
In [66]:
```
columns_list = ['gender', 'SeniorCitizen', 'Partner', 'Dependents',
        'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'Churn']

for col in columns_list:
    print('\n Attribute : ',col,'\n')
    print(telcom[col].value_counts())
```

```
 Attribute :  gender

Male      3549
Female    3483
Name: gender, dtype: int64

 Attribute :  SeniorCitizen

0    5890
1    1142
Name: SeniorCitizen, dtype: int64

 Attribute :  Partner

No     3639
Yes    3393
Name: Partner, dtype: int64

 Attribute :  Dependents

No     4933
Yes    2099
Name: Dependents, dtype: int64

 Attribute :  PhoneService

Yes    6352
No      680
Name: PhoneService, dtype: int64

 Attribute :  MultipleLines

No                  3385
```

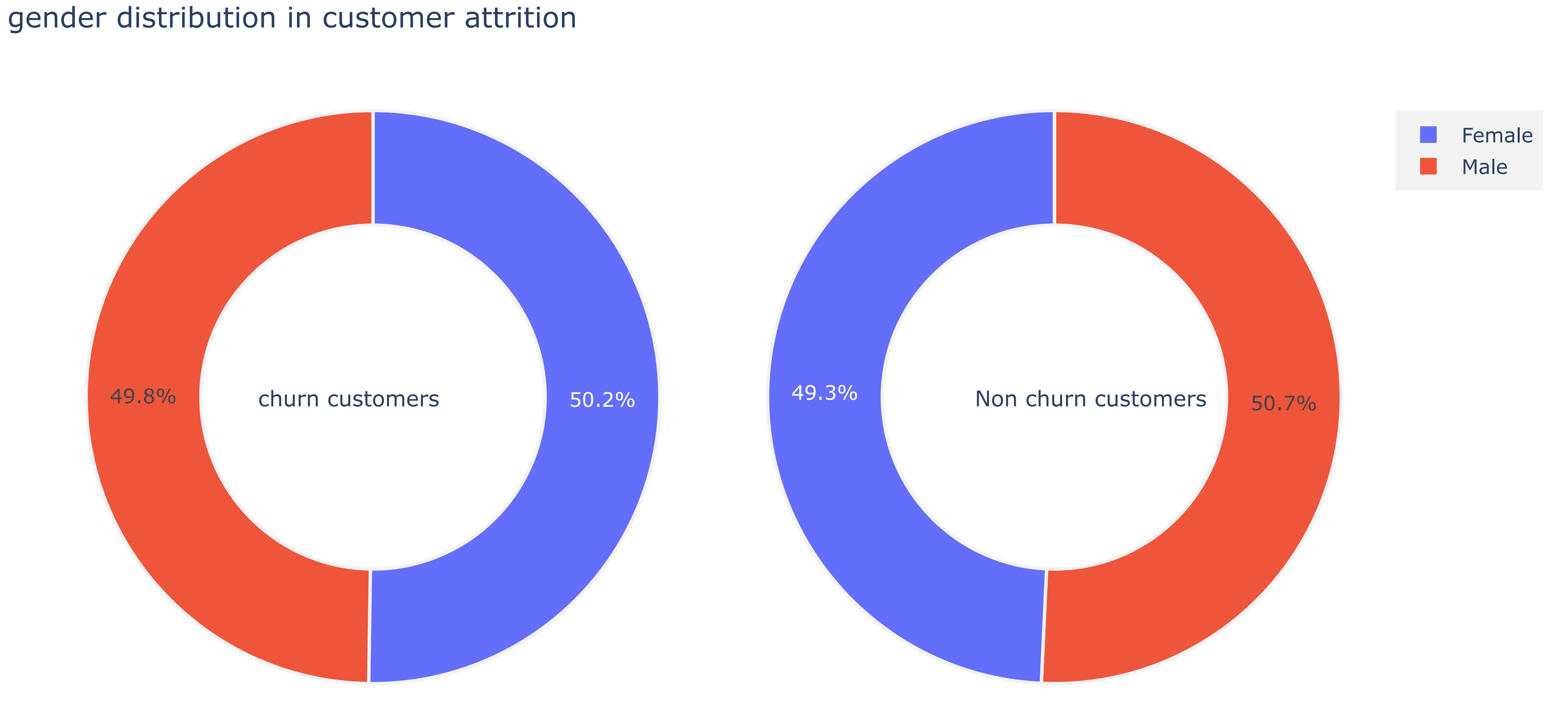
```
Yes                 2967
No phone service     680
Name: MultipleLines, dtype: int64

 Attribute :  InternetService

Fiber optic    3096
DSL            2416
No             1520
Name: InternetService, dtype: int64

 Attribute :  OnlineSecurity

No     5017
Yes    2015
Name: OnlineSecurity, dtype: int64

 Attribute :  OnlineBackup

No     4607
Yes    2425
Name: OnlineBackup, dtype: int64

 Attribute :  DeviceProtection

No     4614
Yes    2418
Name: DeviceProtection, dtype: int64

 Attribute :  TechSupport

No     4992
Yes    2040
Name: TechSupport, dtype: int64

 Attribute :  StreamingTV

No     4329
Yes    2703
Name: StreamingTV, dtype: int64

 Attribute :  StreamingMovies

No     4301
Yes    2731
Name: StreamingMovies, dtype: int64

 Attribute :  Contract

Month-to-month    3875
Two year          1685
One year          1472
Name: Contract, dtype: int64

 Attribute :  PaperlessBilling

Yes    4168
No     2864
Name: PaperlessBilling, dtype: int64

 Attribute :  PaymentMethod

Electronic check             2365
Mailed check                 1604
Bank transfer (automatic)    1542
Credit card (automatic)      1521
Name: PaymentMethod, dtype: int64

 Attribute :  Churn

No     5163
Yes    1869
Name: Churn, dtype: int64
```

In [67]:
```
#Separating churn and non churn customers
churn     = telcom[telcom["Churn"] == "Yes"]
not_churn = telcom[telcom["Churn"] == "No"]

#Separating catagorical and numerical columns
Id_col     = ['customerID']
target_col = ["Churn"]
cat_cols   = telcom.nunique()[telcom.nunique() < 6].keys().tolist()
cat_cols   = [x for x in cat_cols if x not in target_col]
num_cols   = [x for x in telcom.columns if x not in cat_cols + target_col + Id_col]


def plot_pie(column) :

    trace1 = go.Pie(values  = churn[column].value_counts().values.tolist(),
                    labels  = churn[column].value_counts().keys().tolist(),
                    hoverinfo = "label+percent+name",
                    domain  = dict(x = [0,.48]),
                    name    = "Churn Customers",
                    marker  = dict(line = dict(width = 2,
                                               color = "rgb(243,243,243)")
                                  ),
                    hole    = .6
                   )
    trace2 = go.Pie(values  = not_churn[column].value_counts().values.tolist(),
                    labels  = not_churn[column].value_counts().keys().tolist(),
                    hoverinfo = "label+percent+name",
                    marker  = dict(line = dict(width = 2,
                                               color = "rgb(243,243,243)")
                                  ),
                    domain  = dict(x = [.52,1]),
                    hole    = .6,
                    name    = "Non churn customers"
                   )


    layout = go.Layout(dict(title = column + " distribution in customer attrition ",
                            plot_bgcolor  = "rgb(243,243,243)",
                            paper_bgcolor = "rgb(243,243,243)",
                            annotations = [dict(text = "churn customers",
                                                font = dict(size = 13),
                                                showarrow = False,
                                                x = .15, y = .5),
                                           dict(text = "Non churn customers",
                                                font = dict(size = 13),
                                                showarrow = False,
                                                x = .88,y = .5
                                               )
                                          ]
                           )
                      )
    data = [trace1,trace2]
    fig  = go.Figure(data = data,layout = layout)
    py.iplot(fig)
```

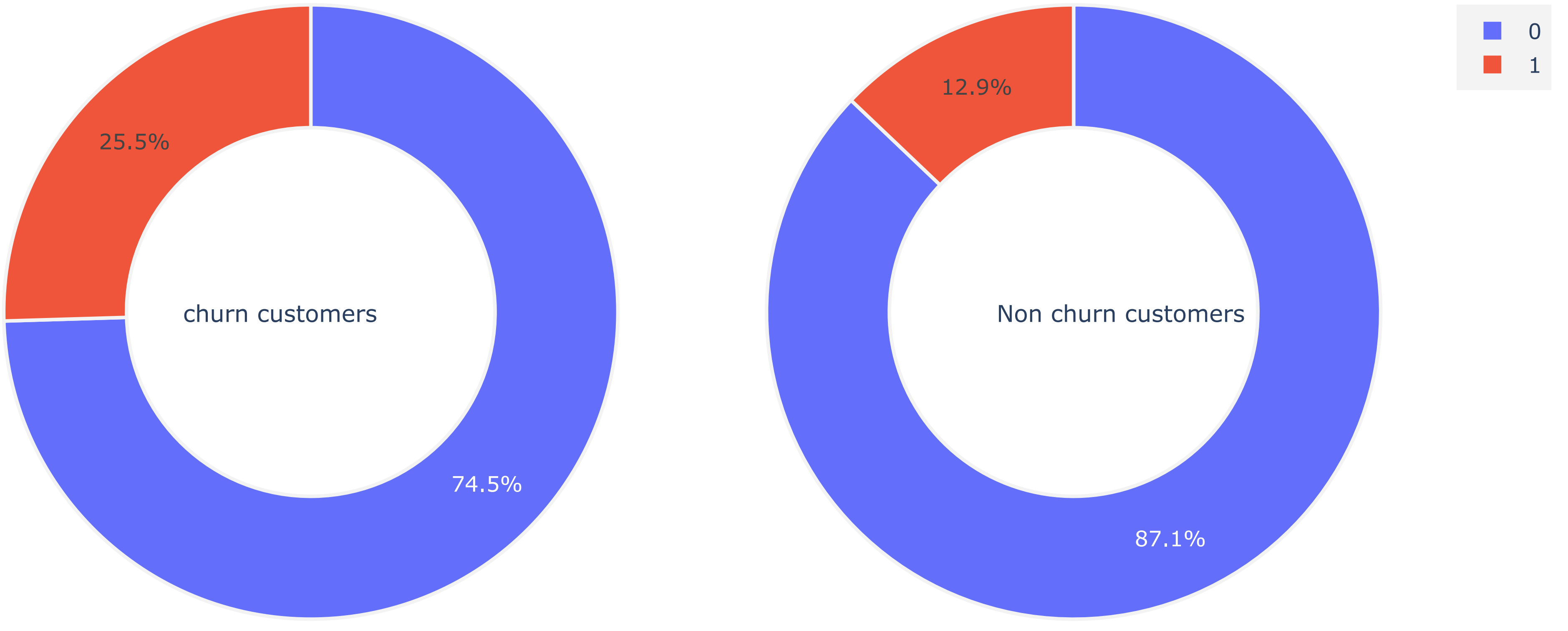
In [68]:
```
lab = telcom["Churn"].value_counts().keys().tolist()
val = telcom["Churn"].value_counts().values.tolist()

trace = go.Pie(labels = lab ,values = val ,
               marker = dict(colors =  [ 'royalblue' ,'lime'],
                             line = dict(color = "white",
                                         width =  1.3)
                            ),
               rotation = 90,hoverinfo = "label+value+text",hole = .5
              )
layout = go.Layout(dict(title = "Customer attrition in data"))

data = [trace]
fig = go.Figure(data = data,layout = layout)
py.iplot(fig)
```



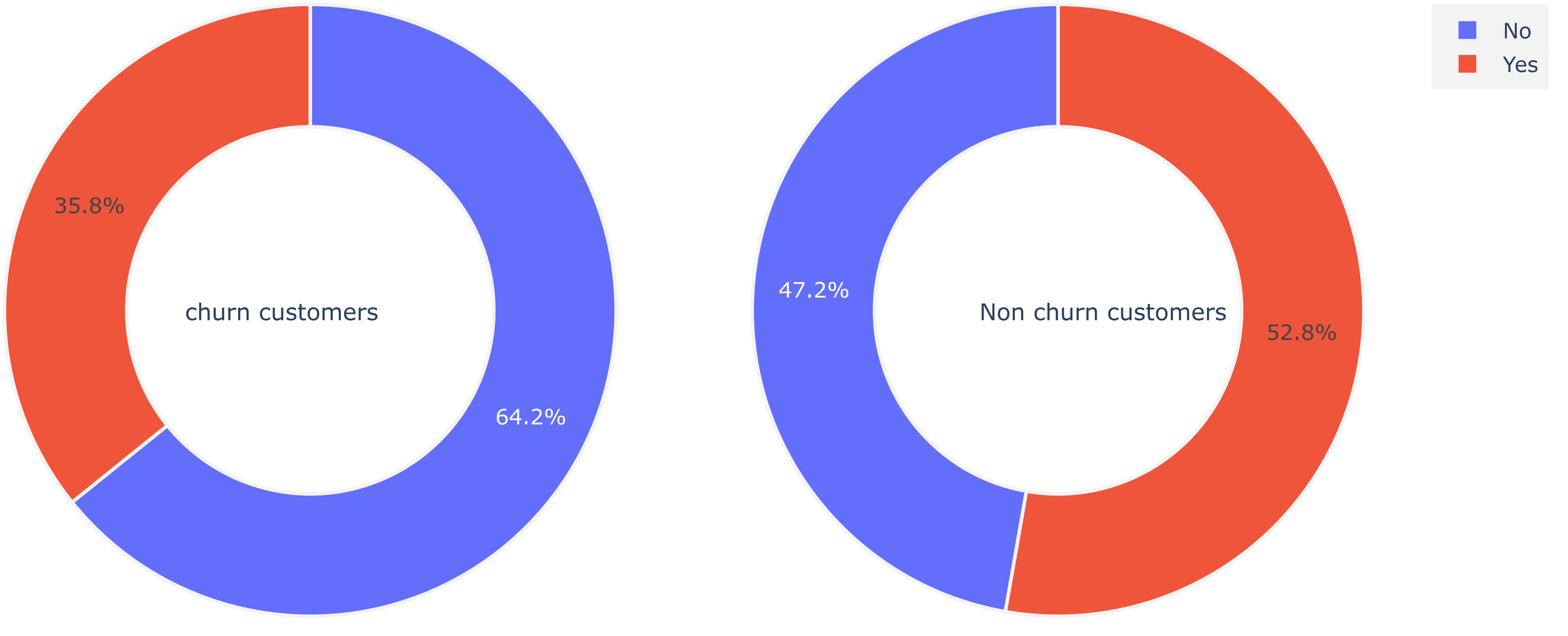
In [69]:
```
#for all categorical columns plot pie
for i in cat_cols :
    plot_pie(i)
```



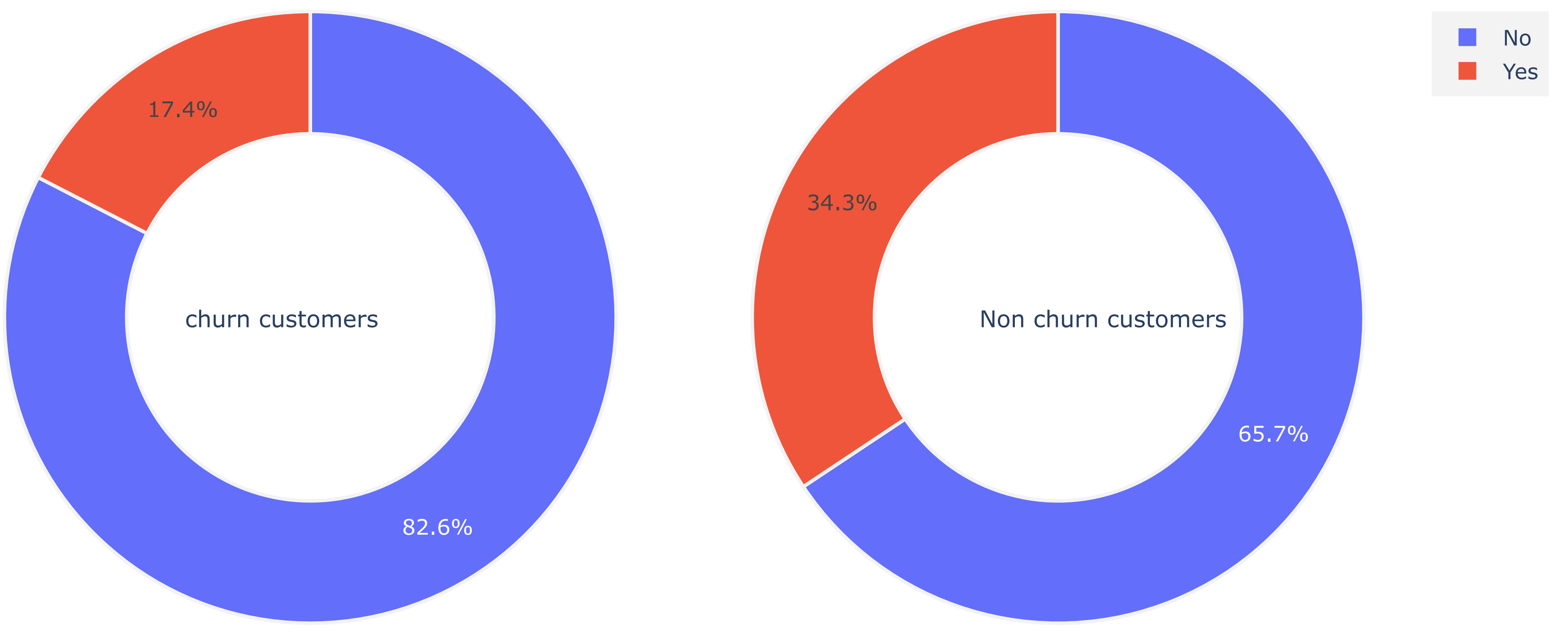
SeniorCitizen distribution in customer attrition



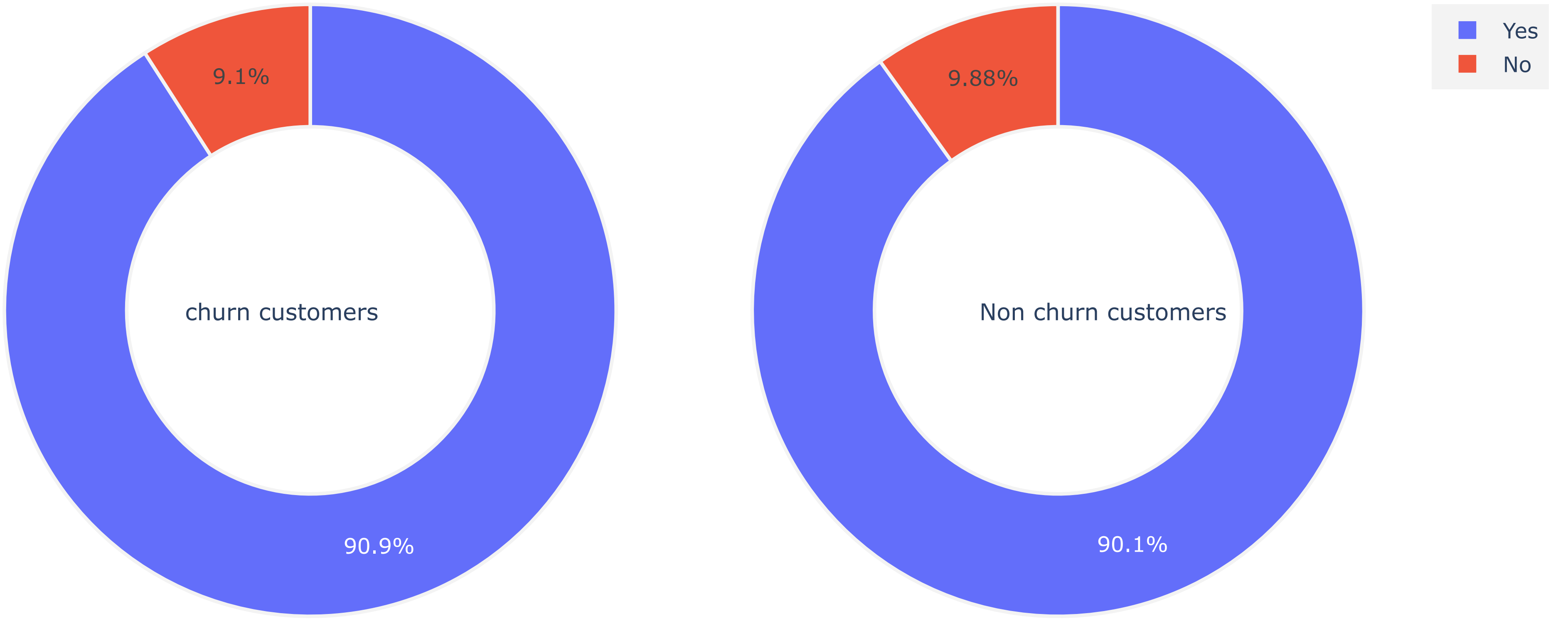
Partner distribution in customer attrition



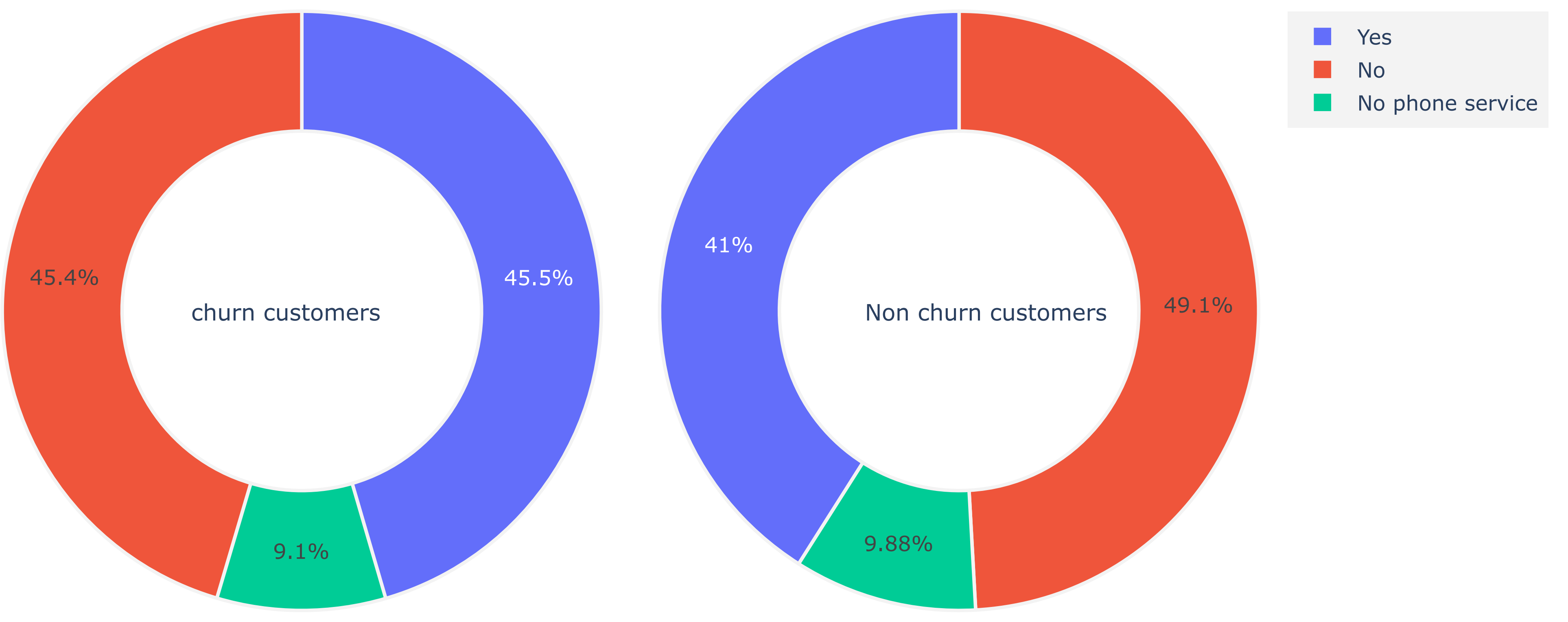
Dependents distribution in customer attrition



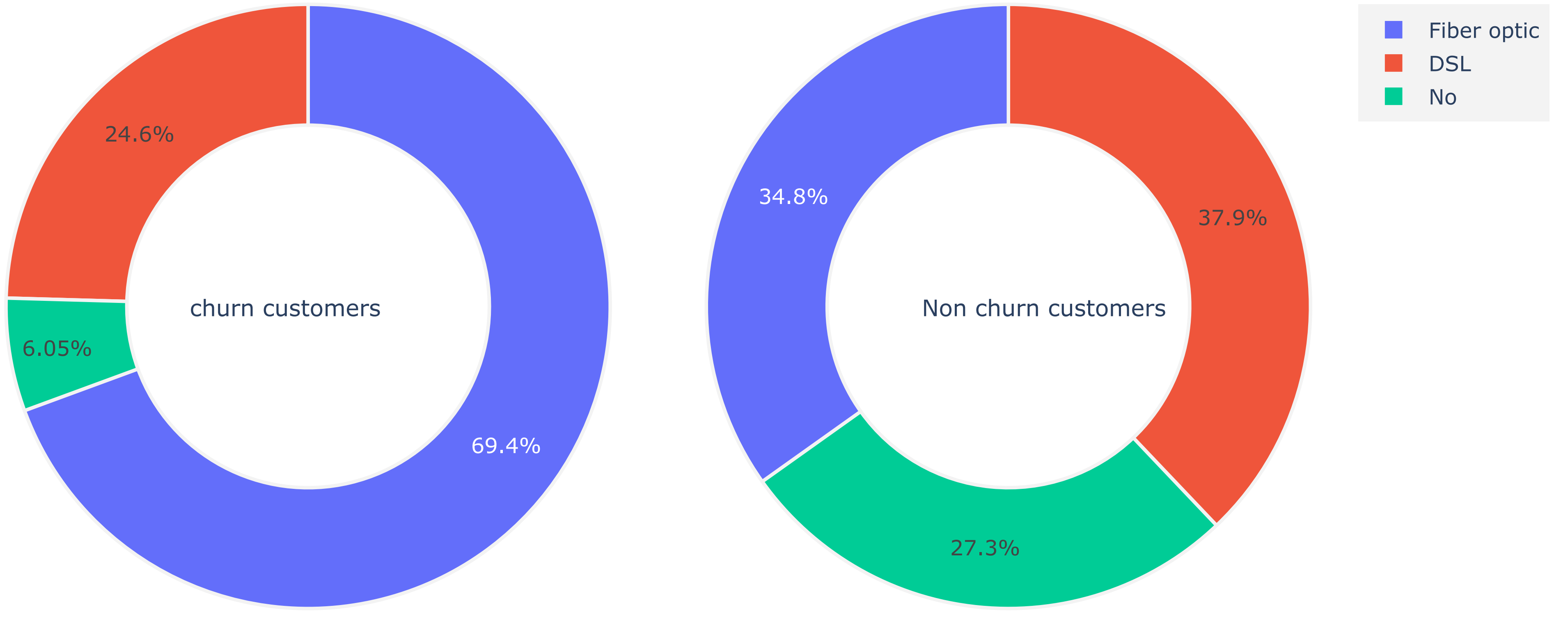
PhoneService distribution in customer attrition



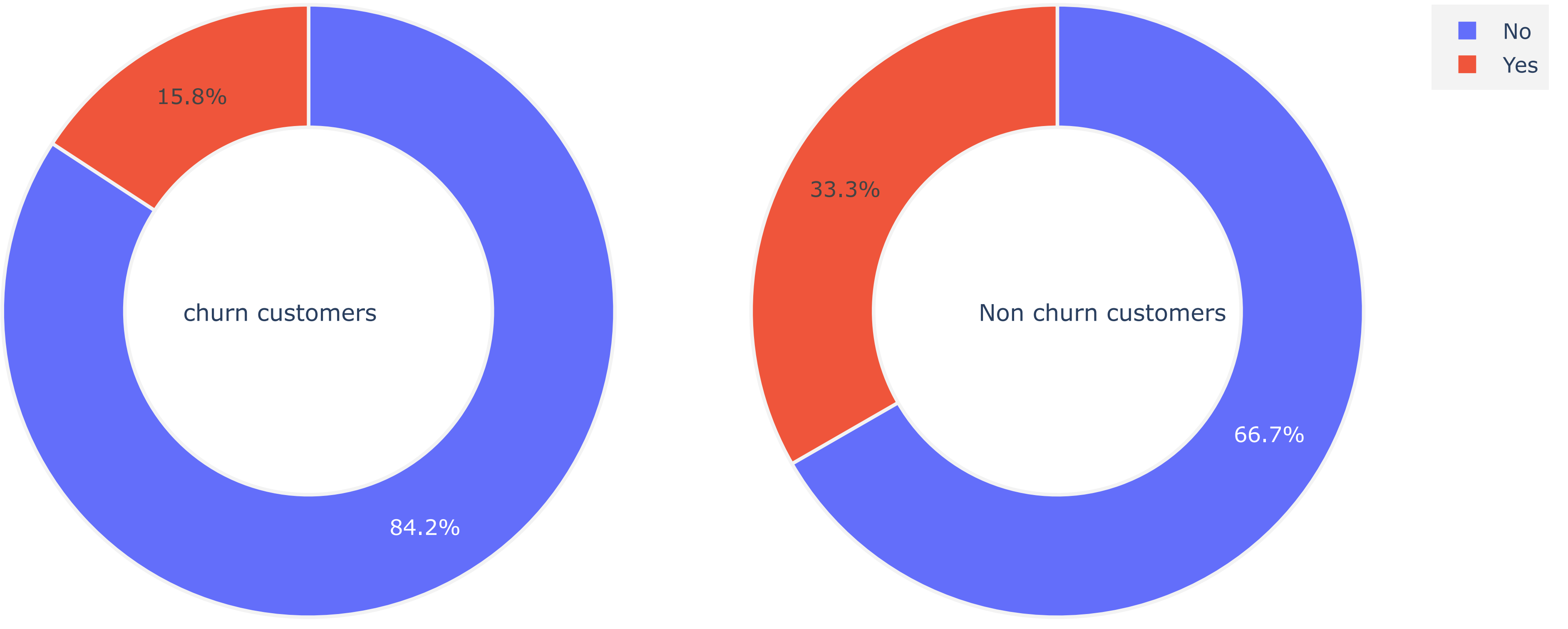
MultipleLines distribution in customer attrition



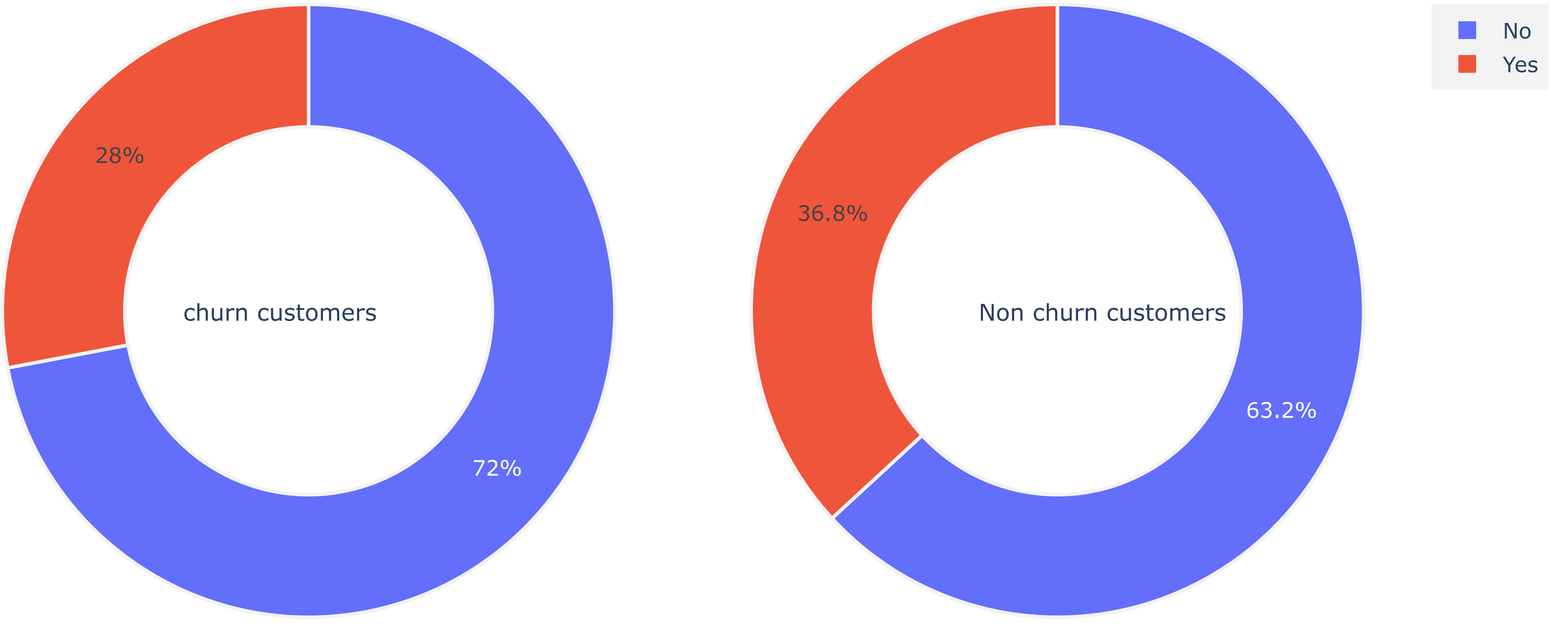
InternetService distribution in customer attrition



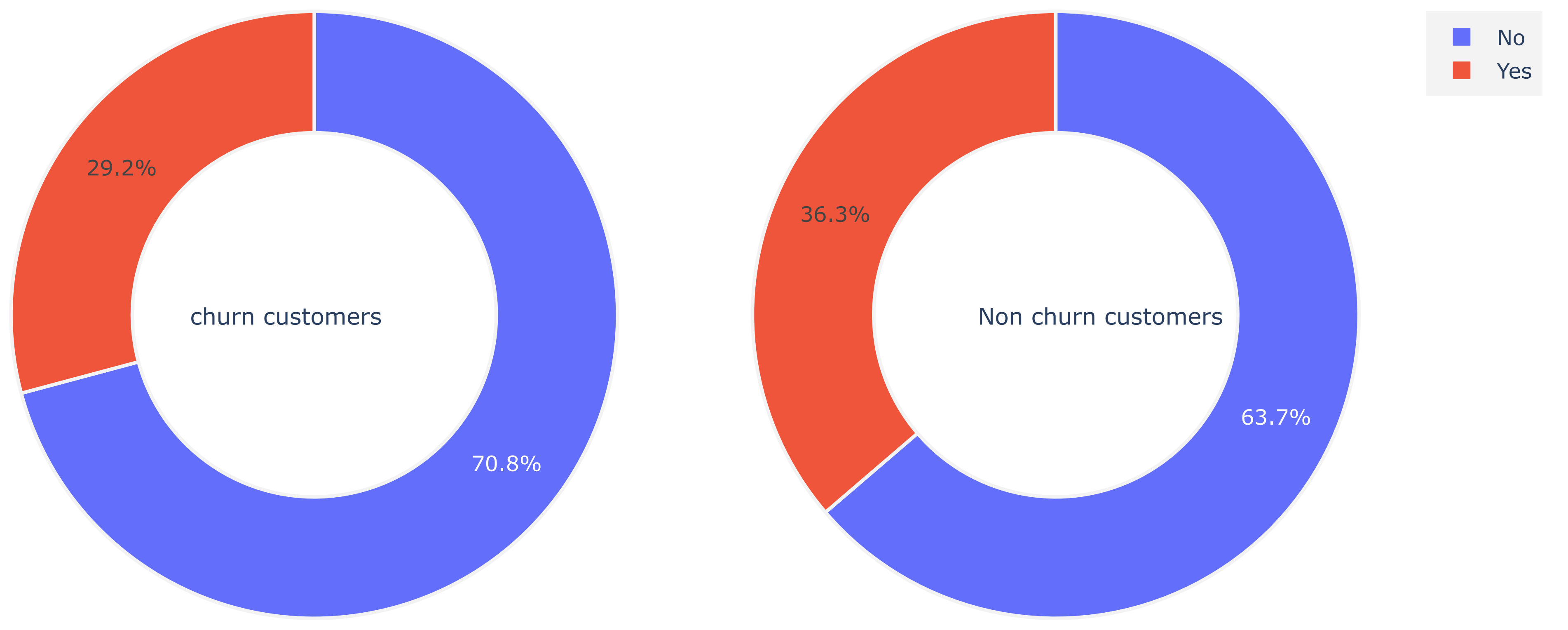
OnlineSecurity distribution in customer attrition



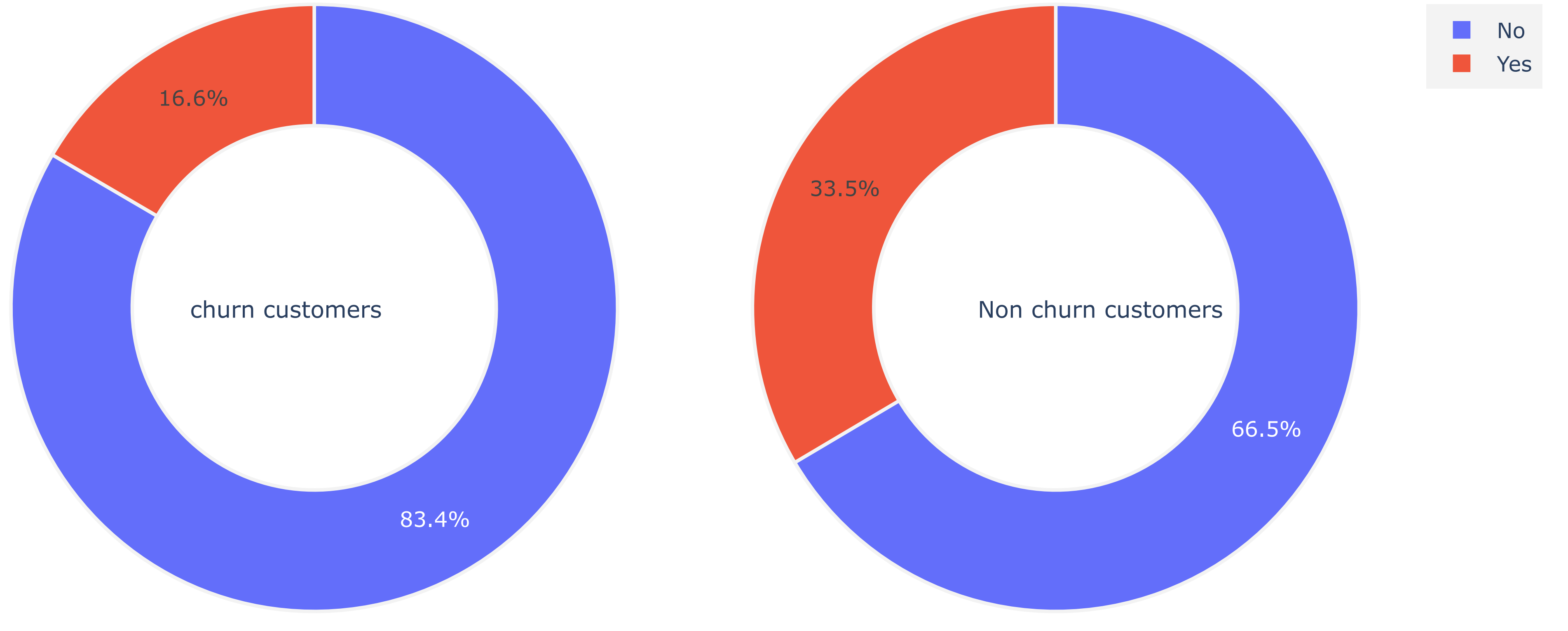
OnlineBackup distribution in customer attrition



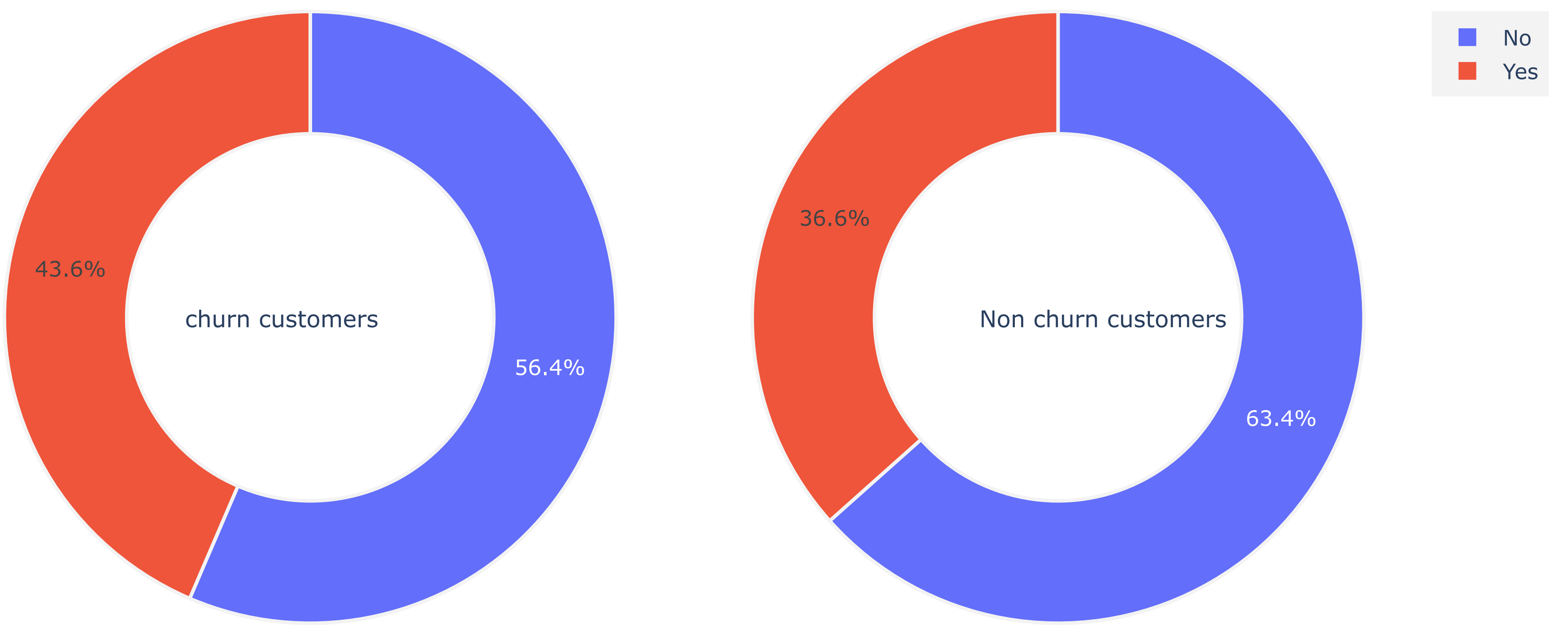
DeviceProtection distribution in customer attrition



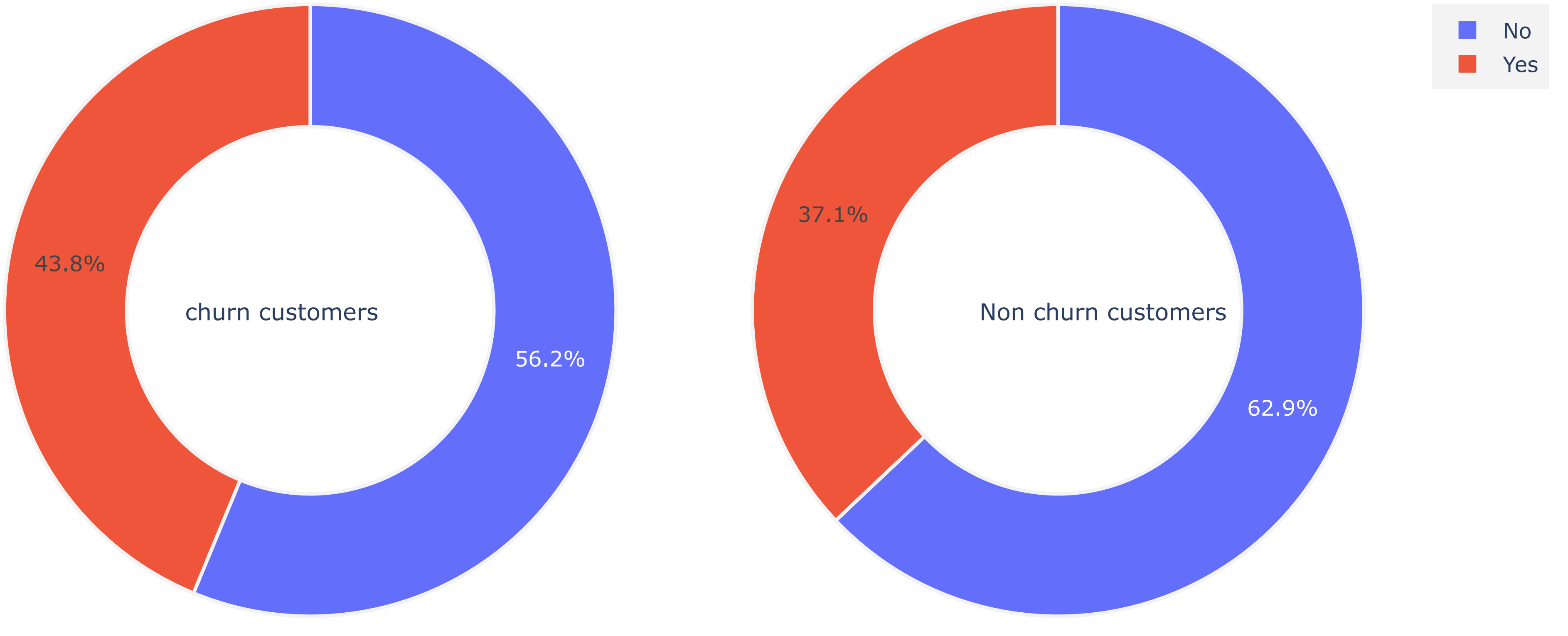
TechSupport distribution in customer attrition

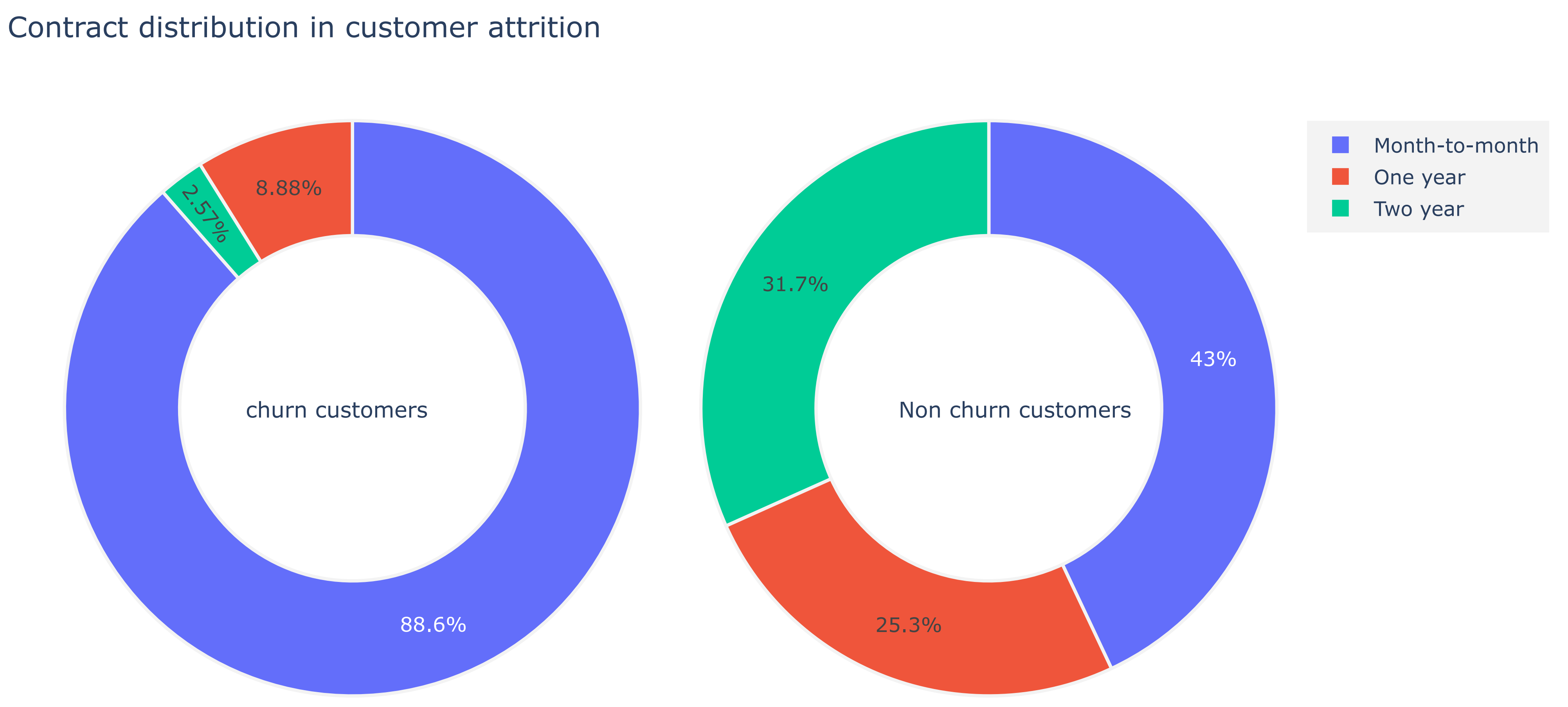


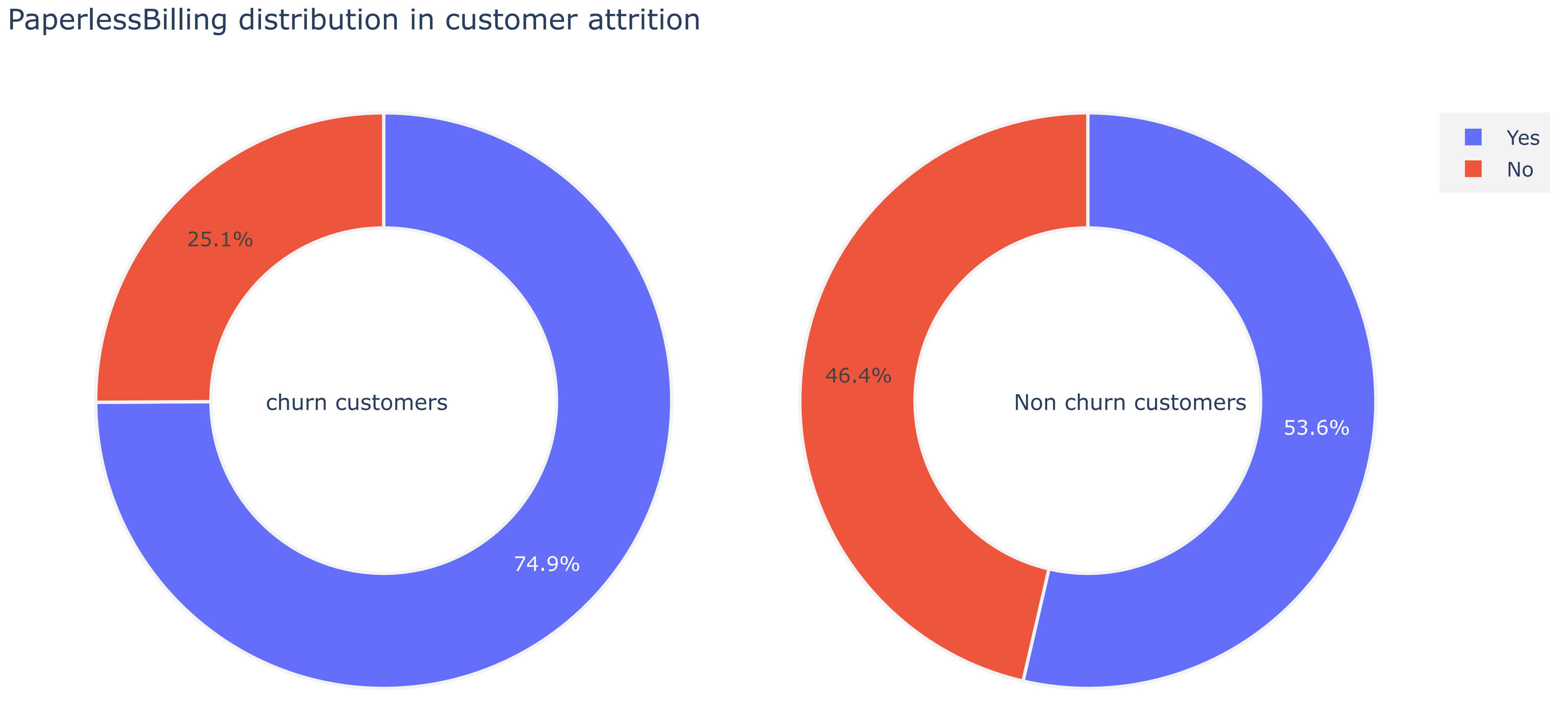
StreamingTV distribution in customer attrition

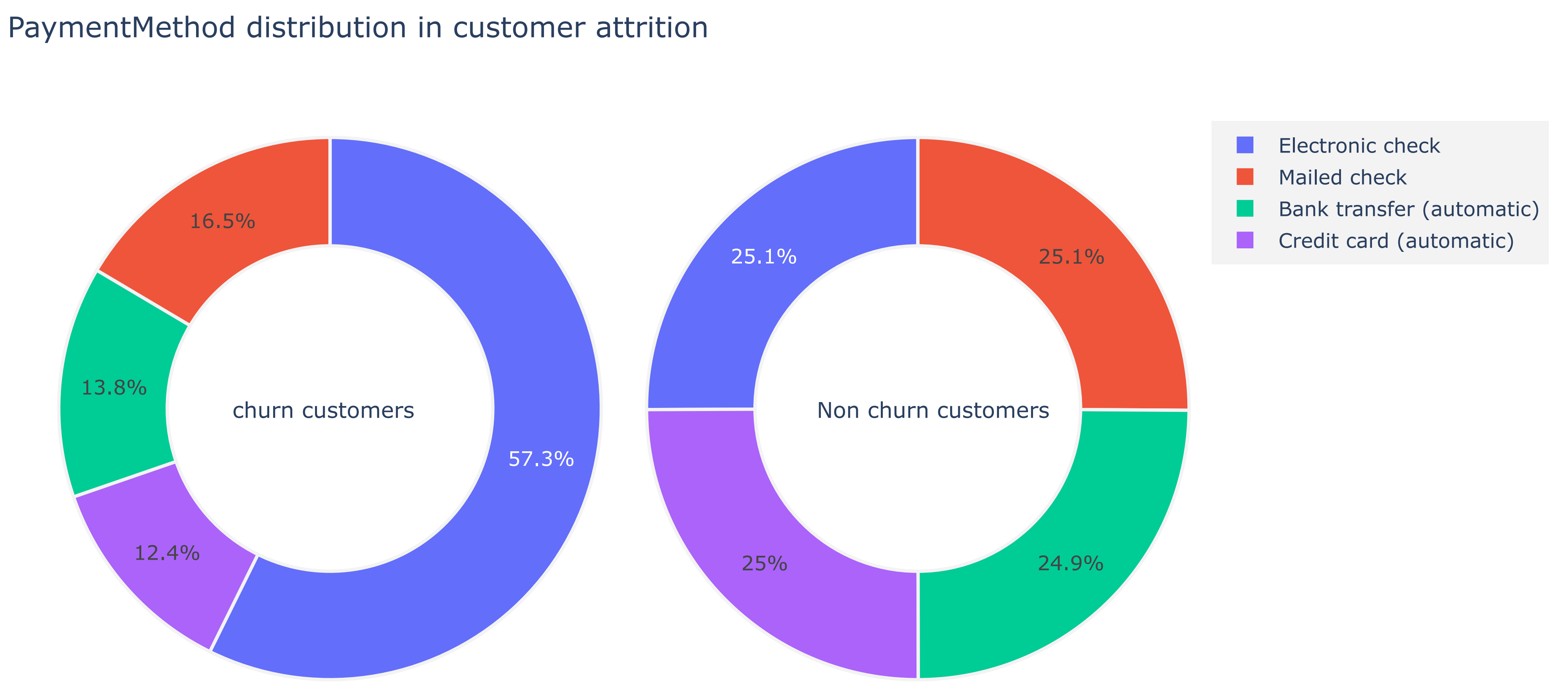


StreamingMovies distribution in customer attrition




Contract distribution in customer attrition
churn customers
88.6%
8.88%
2.57%
Non churn customers
43%
25.3%
31.7%
Month-to-month
One year
Two year

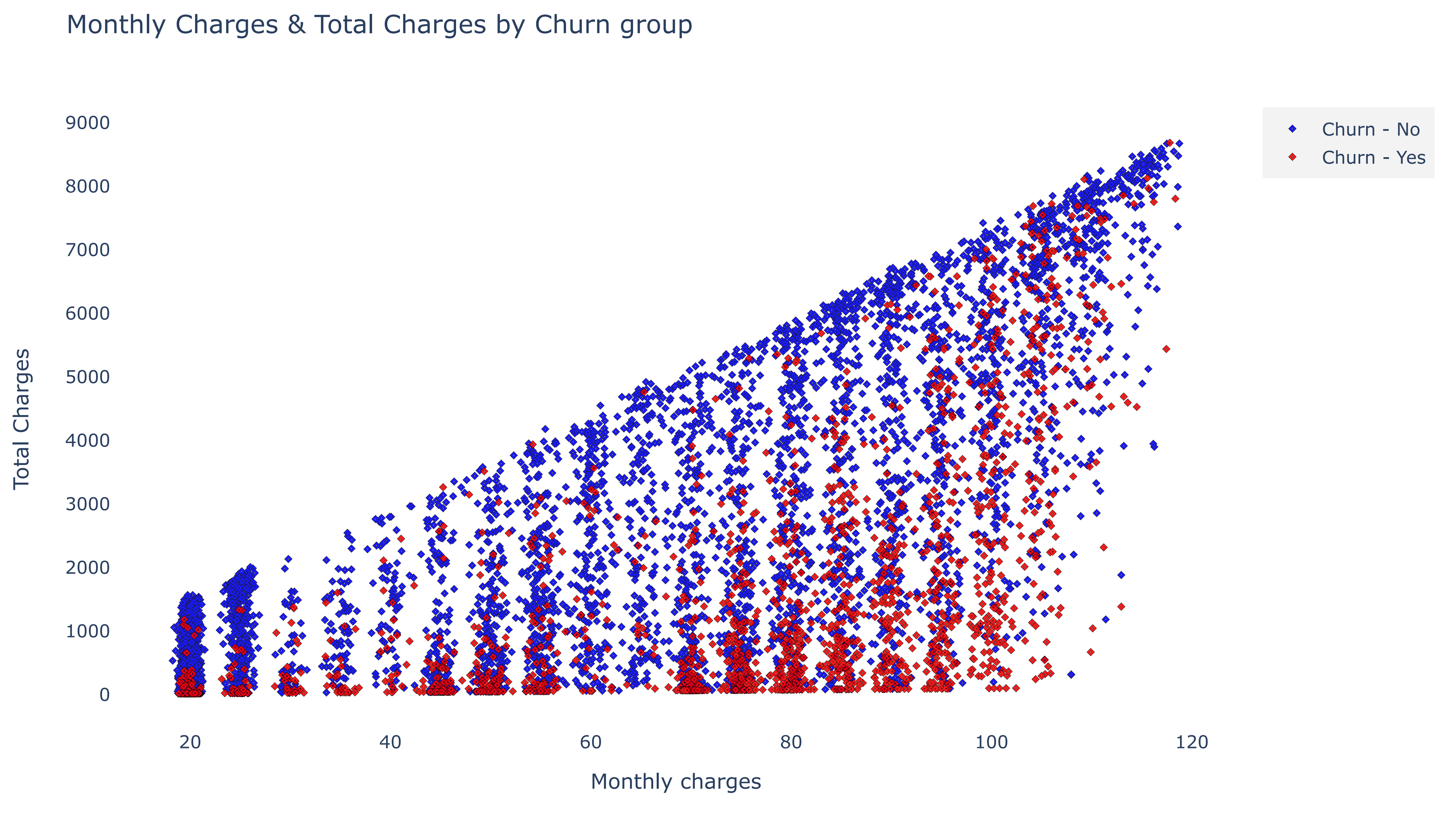

PaperlessBilling distribution in customer attrition
churn customers
74.9%
25.1%
Non churn customers
53.6%
46.4%
Yes
No



Key Takeaways

1. Gender is equally distributed for churn and non churn customers.
2. Majority of Customers donot fall in Seniority Age Group. Senior Churn Customers are more as compared to Non Churn senior Customers.
3. Being a Partner isnt too nuch of a factor for churning customers.
4. Majority of Dependent Customers have high risk of Churn.
5. Phone Service and Multiple Lines Distribution doesnt seem a critical feature in deciding customer churn.
6. Majority of Churned Customers had opted for fiber optics, so we might need to further investigate on this feature.
7. There are chances churn customers are not happy with Online Security and Electronic Check Payment services
8. Month to Month Contract Customers have shown higher chances (~90%) of churning.
9. Streaming Movies, Streaming TV, Device Protection,Online Backup aint much of a factor.

In [70]:
```
#scatter plot monthly charges & total charges by churn group
def plot_churncharges_scatter(churn,color) :
    tracer = go.Scatter(x = telcom[telcom["Churn"] == churn]["MonthlyCharges"],
                        y = telcom[telcom["Churn"] == churn]["TotalCharges"],
                        mode = "markers",marker = dict(line = dict(color = "black",
                                                                   width = .2),
                                                       size = 4 , color = color,
                                                       symbol = "diamond-dot",
                                                      ),
                        name = "Churn - " + churn,
                        opacity = .9
                       )
    return tracer

trace_yes = plot_churncharges_scatter("Yes","red")
trace_no = plot_churncharges_scatter("No","blue")

data2   = [trace_no,trace_yes]

#layout
def layout_title(title) :
    layout = go.Layout(dict(title = title,
                            plot_bgcolor  = "rgb(243,243,243)",
                            paper_bgcolor = "rgb(243,243,243)",
                            xaxis = dict(gridcolor = 'rgb(255, 255, 255)',
                                         title = "Monthly charges",
                                         zerolinewidth=1,ticklen=5,gridwidth=2),
                            yaxis = dict(gridcolor = 'rgb(255, 255, 255)',
                                         title = "Total Charges",
                                         zerolinewidth=1,ticklen=5,gridwidth=2),
                            height = 600
                           )
                      )
    return layout

layout2  = layout_title("Monthly Charges & Total Charges by Churn group")
fig2 = go.Figure(data = data2,layout = layout2)
py.iplot(fig2)
```



We could see that when the monthly charges are more, customer churn out more. The density of non churn customers is more when the total charges is less.

In [71]:
```
telcom['Churn']=telcom['Churn'].replace({'No': 0, 'Yes': 1})
```

We use Chi Square Test to check the correlation between Categorical Features and Binary Response.

In [72]:
```
for x in  [ 'Partner', 'Dependents', 'PhoneService', 'MultipleLines',
           'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
           'StreamingTV', 'StreamingMovies', 'PaperlessBilling']:

    print('==========Chi Square Test for ',x,' and Churn ==========')

    contingency_table=pd.crosstab(telcom[x],telcom["Churn"])

    Observed_Values = contingency_table.values

    #Expected Values
    import scipy.stats
    b=scipy.stats.chi2_contingency(contingency_table)
    Expected_Values = b[3]
    no_of_rows=len(contingency_table.iloc[0:2,0])
    no_of_columns=len(contingency_table.iloc[0,0:2])
    df=(no_of_rows-1)*(no_of_columns-1)

#or
#df=b[2]
#Significance Level 5%
    alpha=0.05

#chi-square statistic - χ2
    from scipy.stats import chi2
    chi_square=sum([(o-e)**2./e for o,e in zip(Observed_Values,Expected_Values)])
    chi_square_statistic=chi_square[0]+chi_square[1]

#critical_value
    critical_value=chi2.ppf(q=1-alpha,df=df)


#p-value
    p_value=1-chi2.cdf(x=chi_square_statistic,df=df)



#compare chi_square_statistic with critical_value and p-value which is the probability of getting chi-square>0.09 (chi
_square_statistic)
    if chi_square_statistic>=critical_value:
        print("Reject H0,There is a relationship between 2 categorical variables - Churn and ",x)
    else:
        print("Retain H0,There is no relationship between 2 categorical variables - Churn and ",x)

    print("\n")
    #if p_value<=alpha:
     #   print("Reject H0,There is a relationship between 2 categorical variables")
    #else:
     #   print("Retain H0,There is no relationship between 2 categorical variables")
```

```
==========Chi Square Test for  Partner  and Churn ==========
Reject H0,There is a relationship between 2 categorical variables - Churn and  Partner


==========Chi Square Test for  Dependents  and Churn ==========
Reject H0,There is a relationship between 2 categorical variables - Churn and  Dependents


==========Chi Square Test for  PhoneService  and Churn ==========
Retain H0,There is no relationship between 2 categorical variables - Churn and  PhoneService


==========Chi Square Test for  MultipleLines  and Churn ==========
Reject H0,There is a relationship between 2 categorical variables - Churn and  MultipleLines


==========Chi Square Test for  OnlineSecurity  and Churn ==========
Reject H0,There is a relationship between 2 categorical variables - Churn and  OnlineSecurity


==========Chi Square Test for  OnlineBackup  and Churn ==========
Reject H0,There is a relationship between 2 categorical variables - Churn and  OnlineBackup


==========Chi Square Test for  DeviceProtection  and Churn ==========
Reject H0,There is a relationship between 2 categorical variables - Churn and  DeviceProtection


==========Chi Square Test for  TechSupport  and Churn ==========
Reject H0,There is a relationship between 2 categorical variables - Churn and  TechSupport


==========Chi Square Test for  StreamingTV  and Churn ==========
Reject H0,There is a relationship between 2 categorical variables - Churn and  StreamingTV


==========Chi Square Test for  StreamingMovies  and Churn ==========
Reject H0,There is a relationship between 2 categorical variables - Churn and  StreamingMovies


==========Chi Square Test for  PaperlessBilling  and Churn ==========
Reject H0,There is a relationship between 2 categorical variables - Churn and  PaperlessBilling
```

For the Continuous Features, we use Correlation Matrix to find out the correlation:

In [73]:
```
telcom[['MonthlyCharges', 'TotalCharges','tenure']].corr()
```

Out[73]:

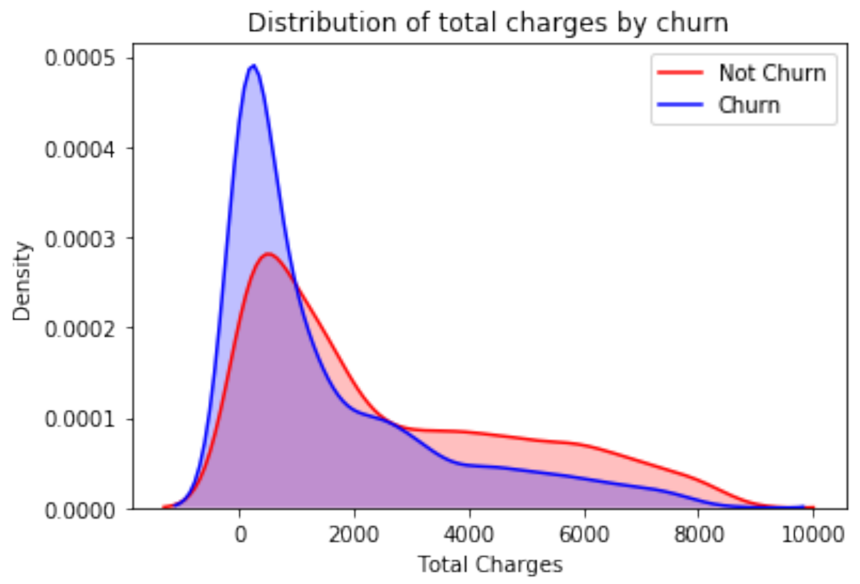
	MonthlyCharges	TotalCharges	tenure
MonthlyCharges	1.000000	0.651065	0.246862
TotalCharges	0.651065	1.000000	0.825880
tenure	0.246862	0.825880	1.000000

There exists strong correlation between Total Charges and Monthly Charges. So ideally we should either remove one of them or we introduce a interaction term. However as of now, we keep this for future reference.

The distribution of Total/Monthly Charges looks skewed both for Churn and Non-Churn Customers from the below KDE plot:

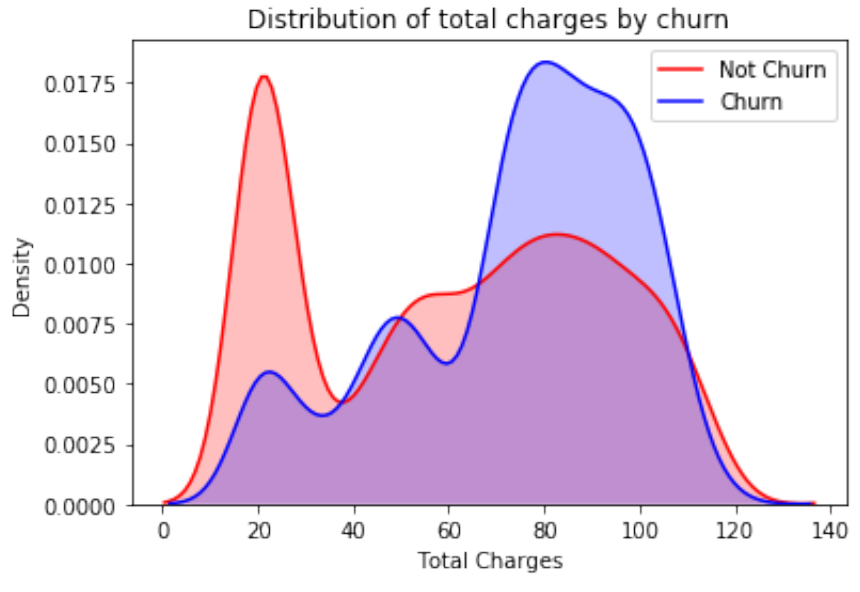
In [74]:
```
ax = sns.kdeplot(telcom.TotalCharges[(telcom["Churn"] == 0) ],
                 color="Red", shade = True)
ax = sns.kdeplot(telcom.TotalCharges[(telcom["Churn"] == 1) ],
                 ax =ax, color="Blue", shade= True)
ax.legend(["Not Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Total Charges')
ax.set_title('Distribution of total charges by churn')
```

Out[74]:
```
Text(0.5, 1.0, 'Distribution of total charges by churn')
```



In [75]:
```
ax = sns.kdeplot(telcom.MonthlyCharges[(telcom["Churn"] == 0) ],
                 color="Red", shade = True)
ax = sns.kdeplot(telcom.MonthlyCharges[(telcom["Churn"] == 1) ],
                 ax =ax, color="Blue", shade= True)
ax.legend(["Not Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Total Charges')
ax.set_title('Distribution of total charges by churn')
```

Out[75]:
```
Text(0.5, 1.0, 'Distribution of total charges by churn')
```



Model Building (Logistic Regression)

In [76]:
```
telcom_dummies = telcom
#telcom_dummies['SeniorCitizen']=telcom_dummies['SeniorCitizen'].replace({0: 'No', 1: 'Yes'})
telcom_dummies = pd.get_dummies(telcom_dummies,columns=['SeniorCitizen','gender', 'SeniorCitizen', 'Partner', 'Depende
nts',
         'PhoneService', 'MultipleLines', 'InternetService',
        'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
        'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
        'PaymentMethod'])

telcom_dummies.drop('customerID', axis=1, inplace=True)

y = telcom_dummies['Churn']
telcom_dummies.drop('Churn', axis=1, inplace=True)
X = telcom_dummies
```

Let's have a look at our features and response dataframes:

In [77]:
```
X.columns
```

Out[77]:
```
Index(['tenure', 'MonthlyCharges', 'TotalCharges', 'SeniorCitizen_0',
       'SeniorCitizen_1', 'gender_Female', 'gender_Male', 'SeniorCitizen_0',
       'SeniorCitizen_1', 'Partner_No', 'Partner_Yes', 'Dependents_No',
       'Dependents_Yes', 'PhoneService_No', 'PhoneService_Yes',
       'MultipleLines_No', 'MultipleLines_No phone service',
       'MultipleLines_Yes', 'InternetService_DSL',
       'InternetService_Fiber optic', 'InternetService_No',
       'OnlineSecurity_No', 'OnlineSecurity_Yes', 'OnlineBackup_No',
       'OnlineBackup_Yes', 'DeviceProtection_No', 'DeviceProtection_Yes',
       'TechSupport_No', 'TechSupport_Yes', 'StreamingTV_No',
       'StreamingTV_Yes', 'StreamingMovies_No', 'StreamingMovies_Yes',
       'Contract_Month-to-month', 'Contract_One year', 'Contract_Two year',
       'PaperlessBilling_No', 'PaperlessBilling_Yes',
       'PaymentMethod_Bank transfer (automatic)',
       'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check'],
      dtype='object')
```

In [78]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=101)

# Running logistic regression model
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
result = model.fit(X_train, y_train)

from sklearn import metrics
prediction_test = model.predict(X_test)
```

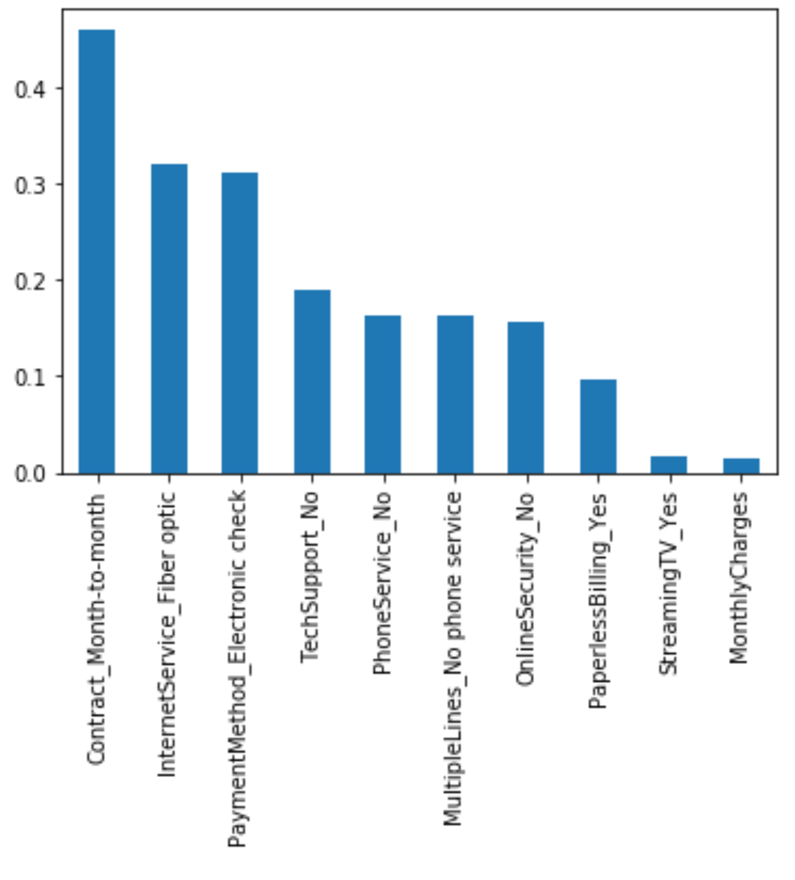
In [79]:
```
from sklearn.metrics import confusion_matrix
```

In [80]:
```
tn, fp, fn, tp = confusion_matrix(y_test, prediction_test).ravel()
print('True Negatives : ' , tn)
print('False Positive : ' , fp)
print('False Negatives : ' , fn)
print('True Positive : ' , tp)
print ('Accuracy : ',  100 * metrics.accuracy_score(y_test, prediction_test))
```

```
True Negatives :  1423
False Positive :  157
False Negatives :  247
True Positive :  283
Accuracy :  80.85308056872039
```

In [81]:
```
# To get the weights of all the variables
weights = pd.Series(model.coef_[0],
                 index=X.columns.values)
print (weights.sort_values(ascending = False)[:10].plot(kind='bar'))
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```



Conclusion

We can see that Contract Type specifically Month-to-Month Contract, Fibre Optic Internet Service and Electronic Check payment Method and Tech Support are key deciding factors in determing the Customer Churn.

We can try below to improve accuracy:

1. Introducing Interaction Terms
2. Advanced ML Algorithms (Decison Trees, Random Forest, Xtreme Gradient Boosting) to get more accurate Customer Churn predictions and important features.