Survival_analysis_project

March 24, 2021

1 Survival Analysis Project: Customer Churn

1.1 Data Summary

The data analyzed here contains information about customer churn for a telecommunicaions company. The data can be downloaded here.

The data includes a number of features about each user, such as their contract type, whether they stream movies and tv, their phone service, and so on.

1.2 Analysis Objectives

The goal of this analysis is to model which features best explain the probabilty of a customer churning in the future.

[1]:
```
# load packages:
import pandas as pd
import numpy as np
from scipy.stats import zscore
import matplotlib.pyplot as plt
import seaborn as sns
from lifelines import KaplanMeierFitter, CoxPHFitter

# visualization
import matplotlib.pyplot as plt
import seaborn as sns
from IPython.display import set_matplotlib_formats

%matplotlib inline

# set to show vector images
set_matplotlib_formats('pdf', 'svg')
```

1.3 Data Overview

[2]:
```
# load in the data:
data = pd.read_csv('telco-customer_churn.csv')
data.shape
```

[2]: (7043, 21)

[3]:
```
# what are our features?
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

First, I'm going to do some basic data cleaning and visualisation:

[4]:
```
# check for any duplicates:
data.duplicated().sum()
```

[4]: 0

[5]:
```
data.head()
```

[5]:
```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes
3  7795-CFOCW    Male              0      No         No      45           No
```

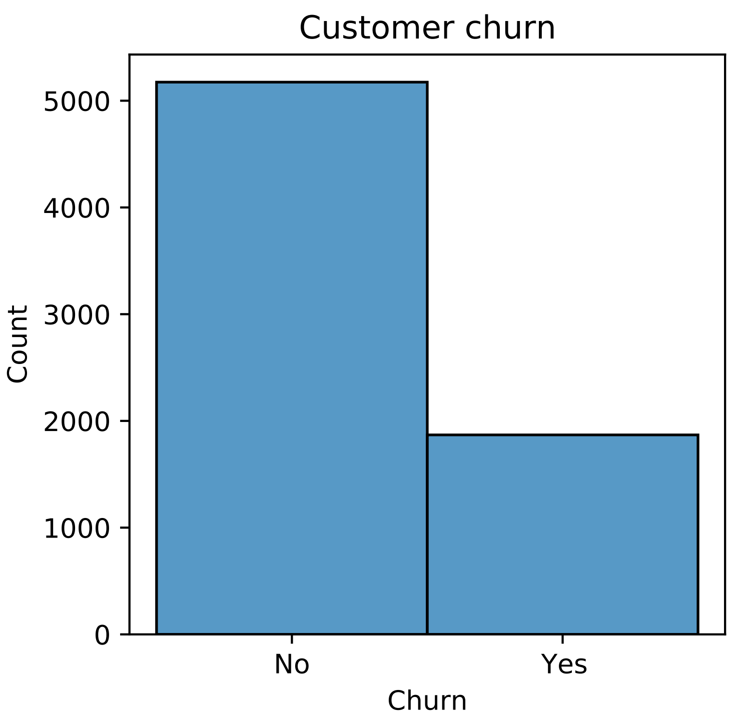
```
4  9237-HQITU  Female              0      No         No       2           Yes

      MultipleLines InternetService OnlineSecurity  … DeviceProtection  \
0  No phone service             DSL             No  …               No
1                No             DSL            Yes  …              Yes
2                No             DSL            Yes  …               No
3  No phone service             DSL            Yes  …              Yes
4                No     Fiber optic             No  …               No

  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0          No          No              No  Month-to-month              Yes
1          No          No              No        One year               No
2          No          No              No  Month-to-month              Yes
3         Yes          No              No        One year               No
4          No          No              No  Month-to-month              Yes

               PaymentMethod MonthlyCharges  TotalCharges Churn
0           Electronic check          29.85         29.85    No
1               Mailed check          56.95        1889.5    No
2               Mailed check          53.85        108.15   Yes
3  Bank transfer (automatic)          42.30       1840.75    No
4           Electronic check          70.70        151.65   Yes

[5 rows x 21 columns]
```

[6]:
```
# any missing values?
data.isna().sum()
```

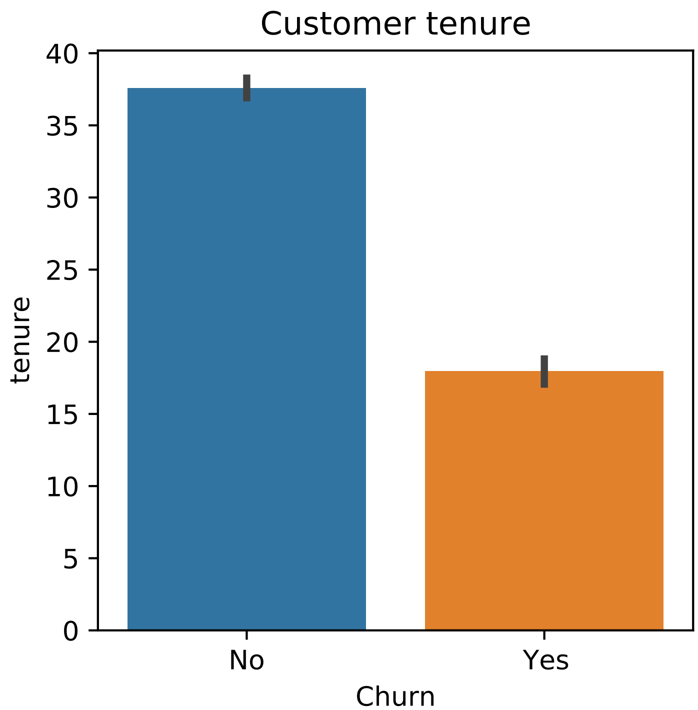
[6]:
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
```

```
TotalCharges        0
Churn               0
dtype: int64
```

[7]:
```
# How many of the customers have churned?
plt.figure(figsize=(4,4))
sns.histplot(data=data, x='Churn')
plt.title('Customer churn')
plt.show()
```



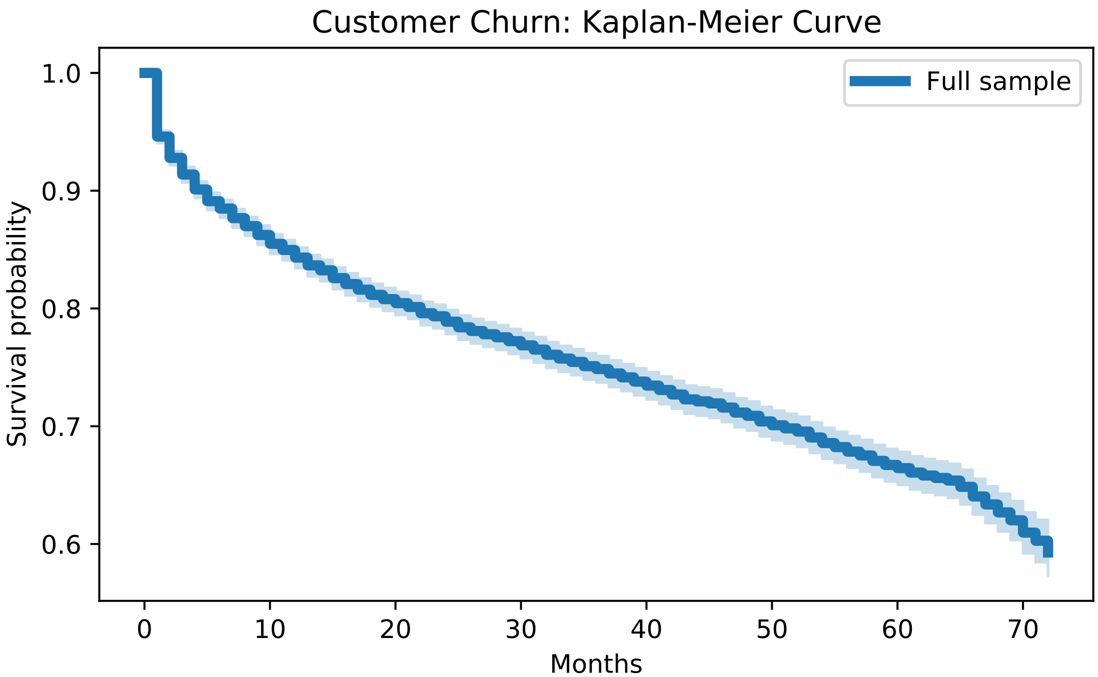
[8]:
```
# How long on average were they/have they been a customer?
plt.figure(figsize=(4,4))
sns.barplot(data=data, x='Churn', y='tenure')
plt.title('Customer tenure')
plt.show()
```



The full sample – Kaplan-Meier curve

[9]:
```
# i'll need to convert churn to a binary variable:
data.replace({"Churn":{"No": 0, "Yes": 1}}, inplace=True)
```

[10]:
```
kmf = KaplanMeierFitter()

kmf.fit(data.tenure, data.Churn, label = 'Full sample')

kmf.plot(linewidth=4, figsize=(7, 4))
plt.title('Customer Churn: Kaplan-Meier Curve')
plt.xlabel('Months')
plt.ylabel('Survival probability')
plt.show()
```



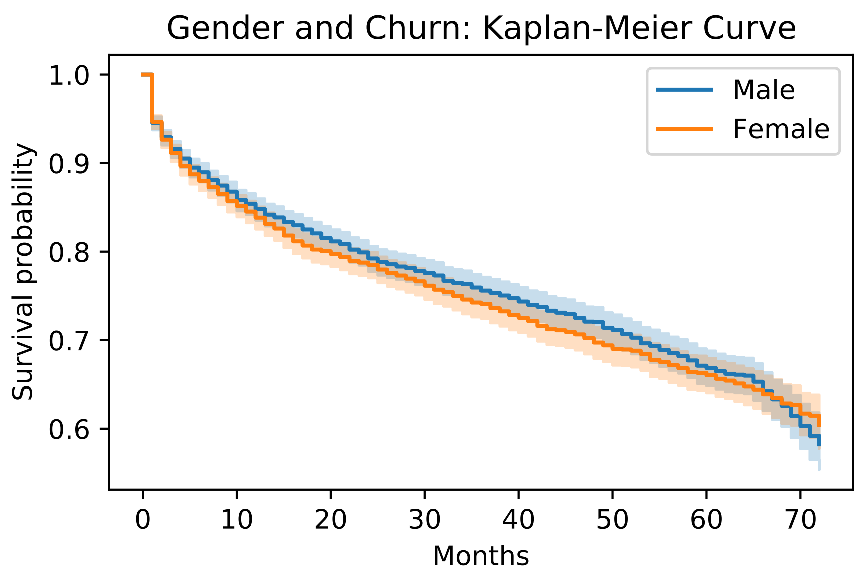
Next, I'm going to visualize the possible effect of a few variables on churn:

Males vs females

From the Kalpan-Meier curves below, gender doesn't appear to have much of an influence on customer churn.

[11]:
```
df1 = data[data.gender == 'Male']
df2 = data[data.gender == 'Female']
```

[12]:
```
kmf.fit(df1.tenure, df1.Churn)
kmf.plot(label = 'Male', figsize=(5,3))
kmf.fit(df2.tenure, df2.Churn)
kmf.plot(label = 'Female', figsize=(5,3))
plt.title('Gender and Churn: Kaplan-Meier Curve')
plt.xlabel('Months')
plt.ylabel('Survival probability')
plt.show()
```

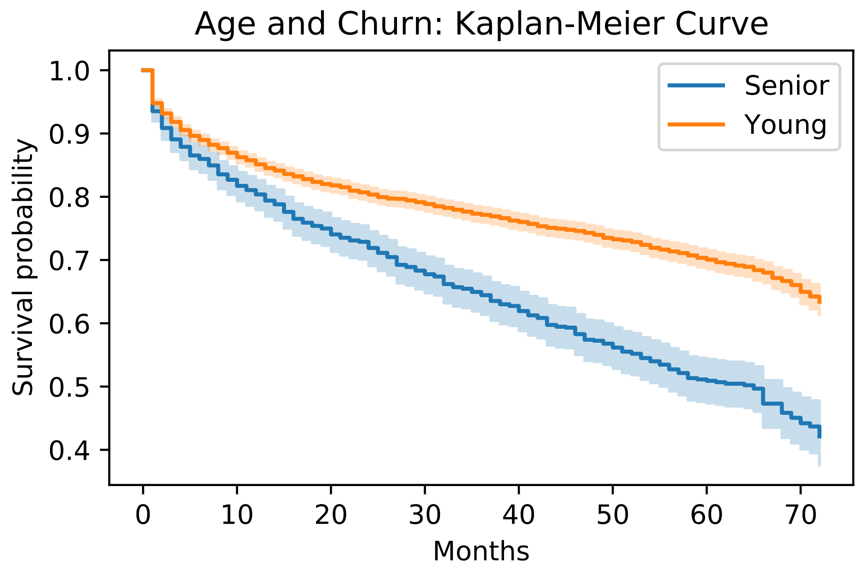


Senior citizen

Being a senior citizen has a large influence on customer churn, likely for multiple reasons!

[13]:
```
df1 = data[data.SeniorCitizen == 1]
df2 = data[data.SeniorCitizen == 0]
```

[14]:
```
kmf.fit(df1.tenure, df1.Churn)
kmf.plot(label = 'Senior', figsize=(5,3))
kmf.fit(df2.tenure, df2.Churn)
kmf.plot(label = 'Young', figsize=(5,3))
plt.title('Age and Churn: Kaplan-Meier Curve')
plt.xlabel('Months')
plt.ylabel('Survival probability')
plt.show()
```

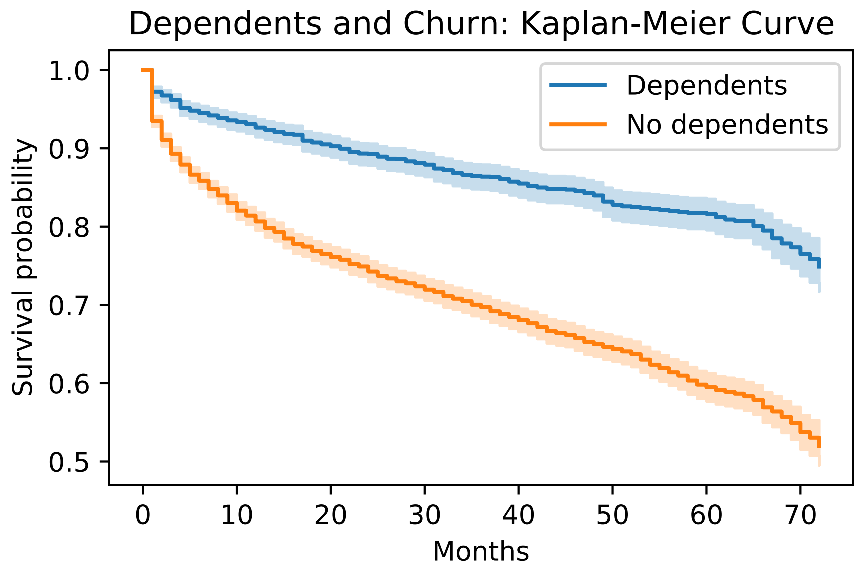


Having dependents

Having dependents makes you much more likely to stay on as a customer.

[15]:
```
df1 = data[data.Dependents == 'Yes']
df2 = data[data.Dependents == 'No']
```

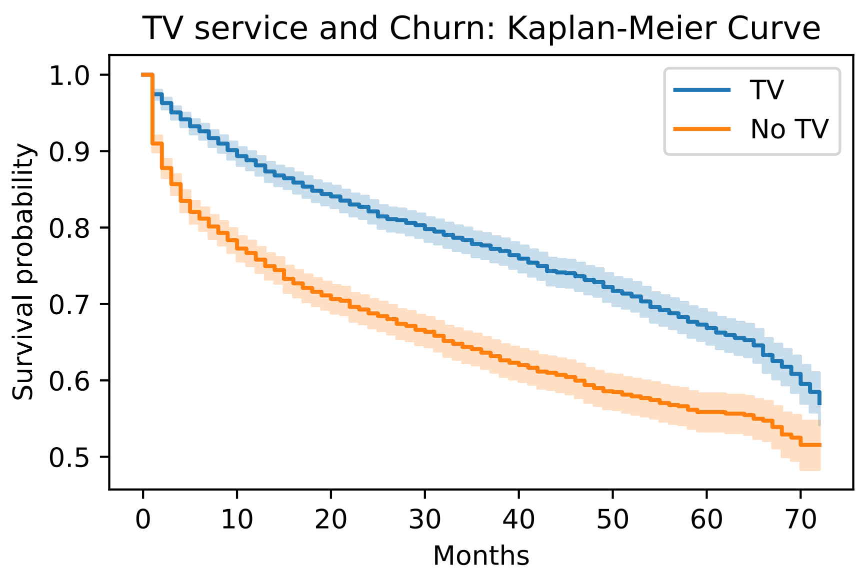
[16]:
```
kmf.fit(df1.tenure, df1.Churn)
kmf.plot(label = 'Dependents', figsize=(5,3))
kmf.fit(df2.tenure, df2.Churn)
kmf.plot(label = 'No dependents', figsize=(5,3))
plt.title('Dependents and Churn: Kaplan-Meier Curve')
plt.xlabel('Months')
plt.ylabel('Survival probability')
plt.show()
```



TV streaming
Finally, what about whether you pay for a for TV streaming? People who pay for TV streaming are less likely to churn, but that benefit does narrow slightly over time.

[17]:
```
df1 = data[data.StreamingTV == 'Yes']
df2 = data[data.StreamingTV == 'No']
```

[18]:
```
kmf.fit(df1.tenure, df1.Churn)
kmf.plot(label = 'TV', figsize=(5,3))
kmf.fit(df2.tenure, df2.Churn)
kmf.plot(label = 'No TV', figsize=(5,3))
plt.title('TV service and Churn: Kaplan-Meier Curve')
plt.xlabel('Months')
plt.ylabel('Survival probability')
plt.show()
```



1.4 CPH Models

To test the hazard rated of our features, I'm now going to fit and compare cox proportional hazard models.

Before building any models, let's take a look at the correlation between my features:

[19]:
```
# dummy code all variables:
data1 = data[['Churn', 'gender', 'SeniorCitizen', 'Dependents',␣
↪'DeviceProtection', 'StreamingTV', 'StreamingMovies']]
data1.head()
```

[19]:
```
   Churn  gender  SeniorCitizen Dependents DeviceProtection StreamingTV  \
0      0  Female              0         No               No          No
1      0    Male              0         No              Yes          No
2      1    Male              0         No               No          No
3      0    Male              0         No              Yes          No
4      1  Female              0         No               No          No

  StreamingMovies
0              No
1              No
2              No
3              No
4              No
```

[20]:

```
data1 = pd.get_dummies(data1, drop_first=True).
 ↪drop(columns=['DeviceProtection_No internet service','StreamingTV_No␣
 ↪internet service','StreamingMovies_No internet service'])
data1['months'] = data.tenure
data1['charges'] = zscore(data.MonthlyCharges)
data1.head()
```

[20]:

```
   Churn  SeniorCitizen  gender_Male  Dependents_Yes  DeviceProtection_Yes  \
0      0              0            0               0                     0
1      0              0            1               0                     1
2      1              0            1               0                     0
3      0              0            1               0                     1
4      1              0            0               0                     0

   StreamingTV_Yes  StreamingMovies_Yes  months   charges
0                0                    0       1 -1.160323
1                0                    0      34 -0.259629
2                0                    0       2 -0.362660
3                0                    0      45 -0.746535
4                0                    0       2  0.197365
```

[21]:

```
cors = data1.corr()
plt.figure(figsize=(5,4))
sns.heatmap(cors)
plt.show()
```

1.4.1 Model 1: Demographics

In this model, I'm just going to include age (senior or not), gender, and any dependents.

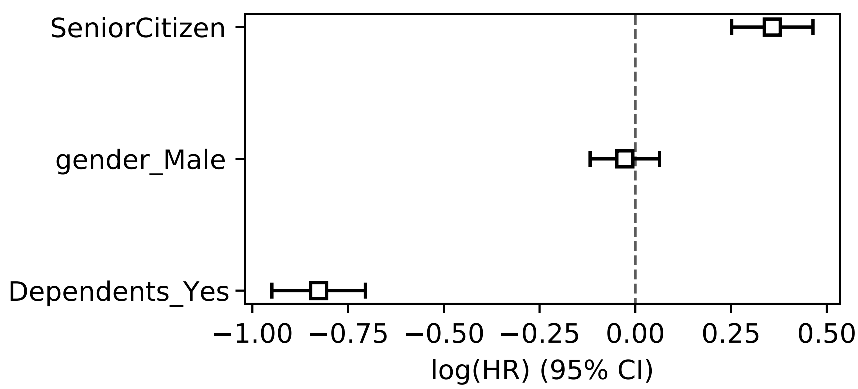
[22]:
```
cph = CoxPHFitter()
cph.fit(data1.
 ↪drop(columns=['charges','DeviceProtection_Yes','StreamingTV_Yes','StreamingMovies_Yes']),␣
 ↪duration_col='months', event_col='Churn')
cph.print_summary(style='ascii')
```

```
<lifelines.CoxPHFitter: fitted with 7043 total observations, 5174 right-censored
observations>
             duration col = 'months'
                event col = 'Churn'
      baseline estimation = breslow
   number of observations = 7043
number of events observed = 1869
   partial log-likelihood = -15502.35
         time fit was run = 2021-03-25 02:08:16 UTC
```

```
---
                 coef  exp(coef)   se(coef)   coef lower 95%   coef upper 95%  
exp(coef) lower 95%  exp(coef) upper 95%
covariate
SeniorCitizen    0.36       1.43       0.05            0.25            0.46
1.29                 1.59
gender_Male     -0.03       0.97       0.05           -0.12            0.06
0.89                 1.07
Dependents_Yes  -0.83       0.44       0.06           -0.95           -0.70
0.39                 0.49

                    z      p   -log2(p)
covariate
SeniorCitizen    6.60 <0.005      34.54
gender_Male     -0.59   0.55       0.85
Dependents_Yes -13.28 <0.005     131.20
---
Concordance = 0.60
Partial AIC = 31010.71
log-likelihood ratio test = 301.37 on 3 df
-log2(p) of ll-ratio test = 213.60
```

[23]:

```
plt.figure(figsize=(4,2))
cph.plot()
plt.show()
```



As we could see from the above kaplan-meier plots, the first model confirms that age and dependents influence hazard risk over time.

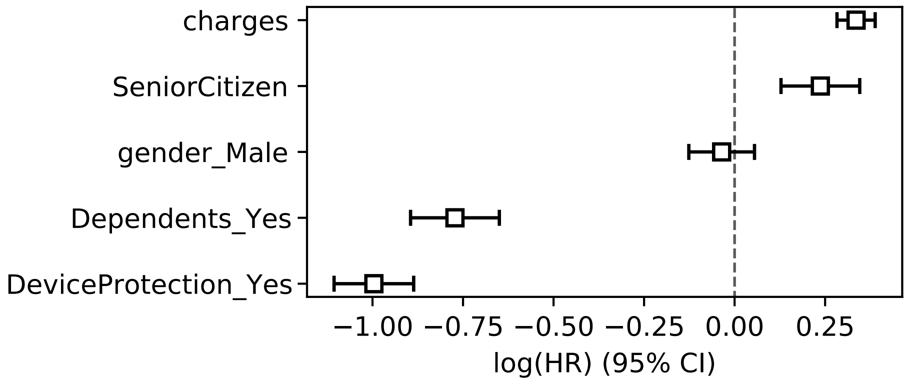
1.4.2 Model 2: Demographics + Device protection + Charges

Same as prior model, now also accounting for whether customers pay for device protection and how much their monthly charges are

[24]:
```
cph = CoxPHFitter()
cph.fit(data1.drop(columns=['StreamingTV_Yes','StreamingMovies_Yes']),␣
↪duration_col='months', event_col='Churn')
cph.print_summary(style='ascii')
```

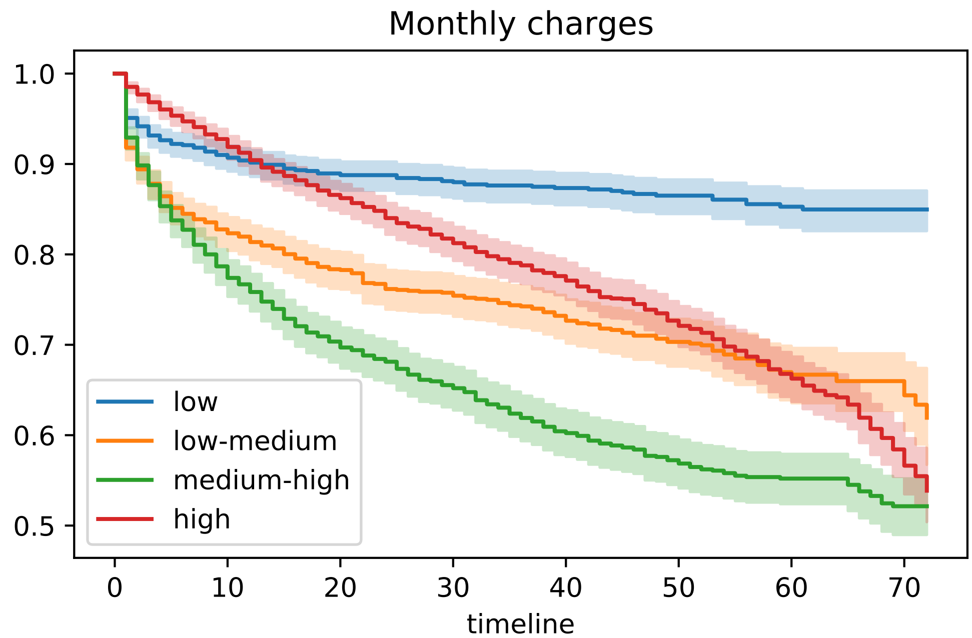
```
<lifelines.CoxPHFitter: fitted with 7043 total observations, 5174 right-censored
observations>
             duration col = 'months'
                event col = 'Churn'
      baseline estimation = breslow
   number of observations = 7043
number of events observed = 1869
   partial log-likelihood = -15323.46
         time fit was run = 2021-03-25 02:08:17 UTC

---
                       coef  exp(coef)   se(coef)   coef lower 95%   coef upper
95%  exp(coef) lower 95%  exp(coef) upper 95%
covariate
SeniorCitizen          0.24       1.27       0.06             0.13
0.35                  1.14                 1.41
gender_Male           -0.04       0.96       0.05            -0.13
0.05                  0.88                 1.06
Dependents_Yes        -0.77       0.46       0.06            -0.89
-0.65                  0.41                 0.52
DeviceProtection_Yes  -1.00       0.37       0.06            -1.11
-0.89                  0.33                 0.41
charges                0.34       1.40       0.03             0.28
0.39                  1.33                 1.47

                          z      p   -log2(p)
covariate
SeniorCitizen          4.27 <0.005      15.65
gender_Male           -0.77   0.44       1.18
Dependents_Yes       -12.35 <0.005     113.94
DeviceProtection_Yes -17.76 <0.005     232.01
charges               12.48 <0.005     116.29
---
Concordance = 0.67
Partial AIC = 30656.92
log-likelihood ratio test = 659.16 on 5 df
-log2(p) of ll-ratio test = 463.34
```

[25]:
```
plt.figure(figsize=(4,2))
cph.plot()
plt.show()
```



Plot the kaplan-meier curve at different levels of monthly charge:

[26]:
```
qs = [0, 0.25, 0.5, 0.75, 1]
labels = ['low','low-medium','medium-high','high']
for q in range(len(qs)-1):
    low_q = data1.charges.quantile(qs[q])
    high_q = data1.charges.quantile(qs[q+1])
    this_data = data1[(data1.charges >= low_q) & (data1.charges < high_q)]
    kmf.fit(this_data.months, event_observed=this_data.Churn)
    kmf.plot(label=labels[q], figsize=(6,3.5))
plt.title('Monthly charges')
plt.show()
```



This model shows that customers who pay for device protection and are less likely to churn, and those who pay a higher monthly charge are more likely to churn. However, this relationship is pretty interesting – customers who have a high monthly charge are actually the least likely to churn within the first year, but then it becomes increasingly likely that they will churn. Customers who have a medium monthly charge are the most likely to churn, while customers who have a very low fee are the least likely to churn.

Overall, this model is a better fit to the data than the prior model as indicated by a lower AIC.

1.4.3 Model 3: All

Same as prior model, now also accounting for whether customers pay for TV and movie streaming

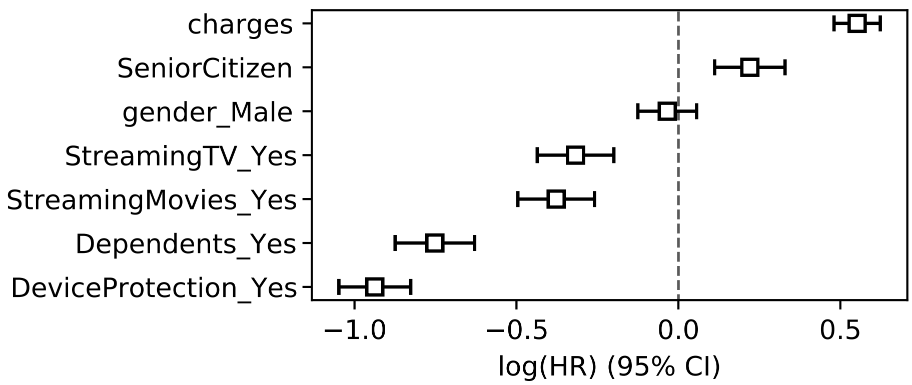
[27]:
```
cph = CoxPHFitter()
cph.fit(data1, duration_col='months', event_col='Churn')
cph.print_summary(style='ascii')
```

```
<lifelines.CoxPHFitter: fitted with 7043 total observations, 5174 right-censored
observations>
             duration col = 'months'
                event col = 'Churn'
      baseline estimation = breslow
   number of observations = 7043
number of events observed = 1869
   partial log-likelihood = -15282.64
         time fit was run = 2021-03-25 02:08:17 UTC

---
```

```
                      coef  exp(coef)   se(coef)   coef lower 95%   coef upper
95%  exp(coef) lower 95%  exp(coef) upper 95%
covariate
SeniorCitizen          0.22       1.25       0.06             0.11
0.33                  1.12                  1.39
gender_Male           -0.03       0.97       0.05            -0.13
0.06                  0.88                  1.06
Dependents_Yes        -0.75       0.47       0.06            -0.87
-0.63                  0.42                  0.53
DeviceProtection_Yes  -0.94       0.39       0.06            -1.05
-0.83                  0.35                  0.44
StreamingTV_Yes       -0.32       0.73       0.06            -0.44
-0.20                  0.65                  0.82
StreamingMovies_Yes   -0.38       0.69       0.06            -0.50
-0.26                  0.61                  0.77
charges                0.55       1.74       0.04             0.48
0.62                  1.62                  1.86

                          z      p   -log2(p)
covariate
SeniorCitizen          3.98 <0.005      13.81
gender_Male           -0.75   0.46       1.13
Dependents_Yes       -12.00 <0.005     107.85
DeviceProtection_Yes -16.56 <0.005     202.23
StreamingTV_Yes       -5.26 <0.005      22.75
StreamingMovies_Yes   -6.25 <0.005      31.21
charges               15.15 <0.005     169.86
---
Concordance = 0.68
Partial AIC = 30579.28
log-likelihood ratio test = 740.80 on 7 df
-log2(p) of ll-ratio test = 514.76
```

[28]:

```
plt.figure(figsize=(4,2))
cph.plot()
plt.show()
```



This final model shows that streaming TV or movies reduces the change of customer churn. This model is only marginally better than Model 2, as indicated by a slightly lower AIC.

1.5 Key Findings

The models show that having a lower monthly fee, having dependents, and having device protection are the main factor that mitigate customer churn. Accounting for more factors such as streaming services and age (senior citizen) also accounts for some variance in when customers churn, but gender is not an influential factor. The final model is likely to be the most appropriate to use.

1.6 Future directions and limitations

There are a number of ways in which these models could be improved. First, I did not account for any possible interactions between the features. For example, perhaps having dependents would reduce the negative impact of having a higher monthly charge rather than those features having an independent influence on customer churn. Second, data could be divided into training and test sets to test how well our features can predict customer churn in unseen data. Finally, more detailed analysis of customer demographics could be helpful, such as exact age, and also behavioral data such as the TV/movie viewing time, for example.

[ ]:

```

```