Customer Churn Case Study

We will take the case study through 3 steps in order to compute a good fit model for predicting a customer churn
Analyzed for candidacy - Senior Manager - Business Intelligence at ZoomInfo - Powered by DiscoverOrg

1. Data Summary and Feature Selection Using three methods
2. Seperating out Train and Test Data
3. Applying model to Train Data and test resulting model on Test Data 80/20 split respectively

In [60]:
```
#Importing required packages to run a Univeariate Feature Selection method
import pandas as pd
import numpy as np

from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.ensemble import ExtraTreesClassifier
```

In [61]:
```
#Loading data
churn_data = pd.read_csv(r"C:\Users\lemic\Downloads\telco-customer-churn\WA_Fn
-UseC_-Telco-Customer-Churn.csv")
churn_data.head()
```

Out[61]:

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

5 rows × 21 columns

In [16]:
```
#print info on dataset
churn_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
customerID          7043 non-null object
gender              7043 non-null object
SeniorCitizen       7043 non-null int64
Partner             7043 non-null object
Dependents          7043 non-null object
tenure              7043 non-null int64
PhoneService        7043 non-null object
MultipleLines       7043 non-null object
InternetService     7043 non-null object
OnlineSecurity      7043 non-null object
OnlineBackup        7043 non-null object
DeviceProtection    7043 non-null object
TechSupport         7043 non-null object
StreamingTV         7043 non-null object
StreamingMovies     7043 non-null object
Contract            7043 non-null object
PaperlessBilling    7043 non-null object
PaymentMethod       7043 non-null object
MonthlyCharges      7043 non-null float64
TotalCharges        7043 non-null float64
Churn               7043 non-null object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB
```

Based on info output, looks like total charges, being a float64 type has either some nulls or non integers values not being recognized

In [20]:
```
churn_data = churn_data.drop('customerID', axis=1) #not needed for analysis
churn_data['TotalCharges'] = pd.to_numeric(churn_data['TotalCharges'], errors = 'coerce') #convert to numeric where possible - got an error for " " nulls so will fill with 0
churn_data[churn_data['TotalCharges'].isna()==True] = 0 # setting nas to zero based on finding running to_numeric error
```

In [21]:
```
#applyign SelectKBest with chi2 fmethod to select best fit features
import matplotlib.pyplot as plt

#extract subset of object data types
obj_churn_data = churn_data.select_dtypes(include=['object']).copy()

# obj_churn_data[obj_churn_data.isnull().any(axis=1)] #no nulls, thats good!

#obj_churn_data.describe()
obj_churn_data_numeric = pd.get_dummies(obj_churn_data)
#obj_churn_data_numeric.info()

int_churn_data = churn_data.select_dtypes(exclude=['object']).copy()

feature_churn = pd.concat([int_churn_data,obj_churn_data_numeric], axis=1)
feature_churn.head()
```

Out[21]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	gender_0	gender_Female	gender_Male
0	0	1	29.85	29.85	0	1	0
1	0	34	56.95	1889.50	0	0	1
2	0	2	53.85	108.15	0	0	1
3	0	45	42.30	1840.75	0	0	1
4	0	2	70.70	151.65	0	1	0

5 rows × 63 columns

In [263]:
```
#setting variables for feature selection
X = feature_churn.iloc[:,0:-2] #indpendent columns for univariate selection
Y = feature_churn.iloc[:,-1] #target column which is last column


BestUnivariateFeatures = SelectKBest(score_func=chi2, k=10)
fit = BestUnivariateFeatures.fit(X,Y)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(X.columns)
featurescores = pd.concat([dfcolumns,dfscores],axis=1)
featurescores.columns = ['feature-univariate-chi2','score']
top_10_univariate_feats = featurescores.nlargest(10, columns = 'score')
top_10_univariate_feats['rank'] = top_10_univariate_feats['score'].rank(ascend
ing=False)
print(top_10_univariate_feats)
```

```
                 feature-univariate-chi2          score  rank
3                           TotalCharges  624292.003004   1.0
1                                 tenure   16278.923685   2.0
2                         MonthlyCharges    3733.878622   3.0
49                 Contract_Month-to-month     519.895311   4.0
51                       Contract_Two year     485.007178   5.0
58        PaymentMethod_Electronic check     426.422767   6.0
25                     OnlineSecurity_No     416.716774   7.0
37                        TechSupport_No     406.645334   8.0
22           InternetService_Fiber optic     374.476216   9.0
29                       OnlineBackup_No     284.531747  10.0
```

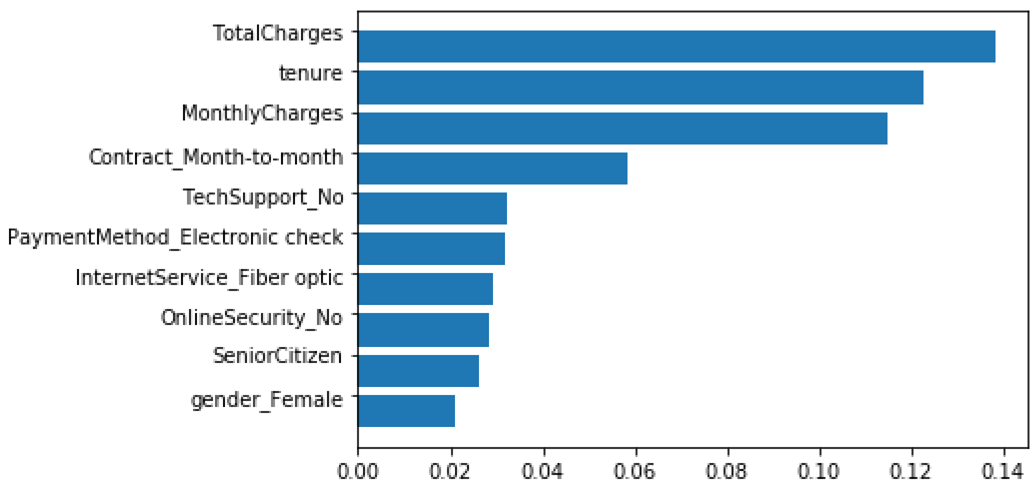
We can see that the top three most prominent features that help determine customer churn (value = 1) are Total charges, Tenure, and Monthly Charges

The trailing features that could play an important part in the final stretch of the predicitive model are whether they have: 49 Contract_Month-to-month 519.895311 4.0 51 Contract_Two year 485.007178 5.0 58 PaymentMethod_Electronic check 426.422767 6.0 25 OnlineSecurity_No 416.716774 7.0 37 TechSupport_No 406.645334 8.0 22 InternetService_Fiber optic 374.476216 9.0 29 OnlineBackup_No 284.531747 10.0

In [68]:
```
#feature detection/selection using extratreesclassifier method
model_churn = ExtraTreesClassifier(n_estimators = 100) #100 trees in forest
model_churn.fit(X,Y)
#print(model_churn.feature_importances_) #inbuilt class from sklearn
feat_importance = pd.Series(model_churn.feature_importances_,index=X.columns)
feat_importance = pd.DataFrame(feat_importance)
feat_importance.reset_index(inplace = True)
feat_importance.columns = ['feature-extra-trees','Classifier Importance']
feat_tree_top10 = feat_importance.nlargest(10, columns = 'Classifier Importanc
e')
plt.barh(feat_tree_top10['feature-extra-trees'], feat_tree_top10['Classifier I
mportance'],align='edge')
plt.gca().invert_yaxis()
plt.show

#curious about less important features? print below by uncommenting and runnin
g
#print(feat_importance.nsmallest(40, columns = 'Classifier Importance'))
```

Out[68]:
```
<function matplotlib.pyplot.show(*args, **kw)>
```



We now have the top 12 important features using the ensemble extra trees classifiers within a forest with 100 trees

In [69]:
```
#compare of univariate vs ensemble method

pd.concat([top_10_univariate_feats,feat_tree_top10], axis = 1).sort_values(by
='Classifier Importance', ascending=False) # allows comparison between univari
ate feature selection vs extratreesclassifier feature detection
```

Out[69]:

	feature-univariate-chi2	score	rank	feature-extra-trees	Classifier Importance
3	TotalCharges	624292.003004	1.0	TotalCharges	0.138462
1	tenure	16278.923685	2.0	tenure	0.122828
2	MonthlyCharges	3733.878622	3.0	MonthlyCharges	0.114840
49	Contract_Month-to-month	519.895311	4.0	Contract_Month-to-month	0.058625
37	TechSupport_No	406.645334	8.0	TechSupport_No	0.032556
58	PaymentMethod_Electronic check	426.422767	6.0	PaymentMethod_Electronic check	0.031774
22	InternetService_Fiber optic	374.476216	9.0	InternetService_Fiber optic	0.029503
25	OnlineSecurity_No	416.716774	7.0	OnlineSecurity_No	0.028391
0	NaN	NaN	NaN	SeniorCitizen	0.026131
5	NaN	NaN	NaN	gender_Female	0.021046
29	OnlineBackup_No	284.531747	10.0	NaN	NaN
51	Contract_Two year	485.007178	5.0	NaN	NaN

Based on findings above, I will train a model based on the top matching features, which are:

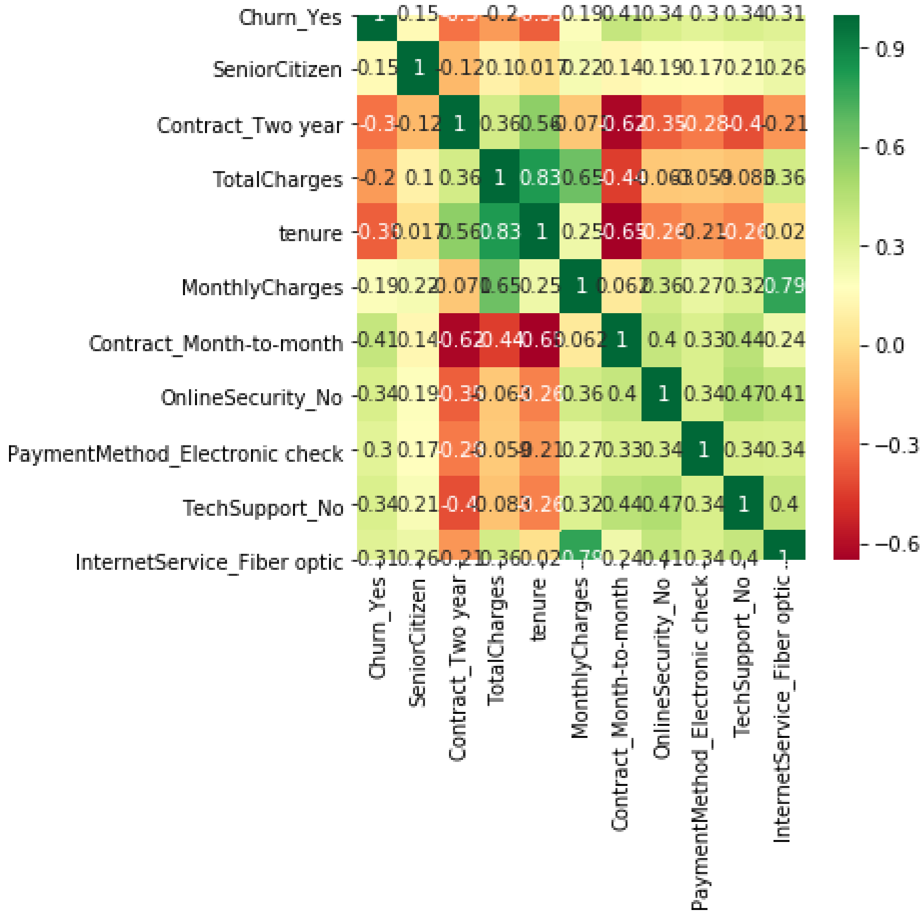
1. TotalCharges 624292.003004 1.0 TotalCharges 0.136892
2. tenure 16278.923685 2.0 tenure 0.123686
3. MonthlyCharges 3733.878622 3.0 MonthlyCharges 0.115721
4. Contract_Month-to-month 519.895311 4.0 Contract_Month-to-month 0.060624
5. OnlineSecurity_No 416.716774 7.0 OnlineSecurity_No 0.031221
6. PaymentMethod_Electronic check 426.422767 6.0 PaymentMethod_Electronic check 0.029601
7. TechSupport_No 406.645334 8.0 TechSupport_No 0.028722
8. InternetService_Fiber optic 374.476216 9.0 InternetService_Fiber optic 0.026591

In [234]:
```
#As a treat, let's show a correlation heat map to see how those features affec
t the churn rate
import seaborn as sns
```

In [261]:
```
selected_feats_churn = feature_churn[['Churn_Yes','SeniorCitizen','Contract_Tw
o year', 'TotalCharges','tenure','MonthlyCharges','Contract_Month-to-month','O
nlineSecurity_No','PaymentMethod_Electronic check','TechSupport_No','InternetS
ervice_Fiber optic']]
cormat = selected_feats_churn.corr()
print(len(cormat))
```

```
11
```

In [262]:
```
top_corr_features = corrmat.index
g =sns.heatmap(feature_churn[top_corr_features].corr(),annot=True,cmap="RdYlG
n")
#top and bottom row cut off due to unstable seaborn and matplotlib with latest
update. could revert to older version of matplotlib, but we'll roll with this
 for now.
```



Of the top 10 features identified, 7 have a positive correlation to a customer churning and 3 have a negative correlation

Summary of Feature Selection

Based on findings, an analyst would find most value building visualizations or reports that target the 8 features identified above, and when there is a deviation above the median for numerical measurements, then a flag or warning should appear next to that customer record. This would include TotalCharges, Tenure, MonthlyCharges. For the categorical variables, having a contract month-to-month and a combination of one ore more of the above breaching a median, would flag the customer as a potential churn, and allow sales rep to reach out and attempt a conversion to contract vs month-to-month. The same would go for all other categorical features such as tech support and online security. Improving the online security of a user, and tech support are simple steps that the company can take to retain more customers as shown below on the correlation map. (having online security and tech support reduces churn)

```
Churn_Yes              1.000000
OnlineSecurity_Yes    -0.170573
TechSupport_Yes       -0.164016
```

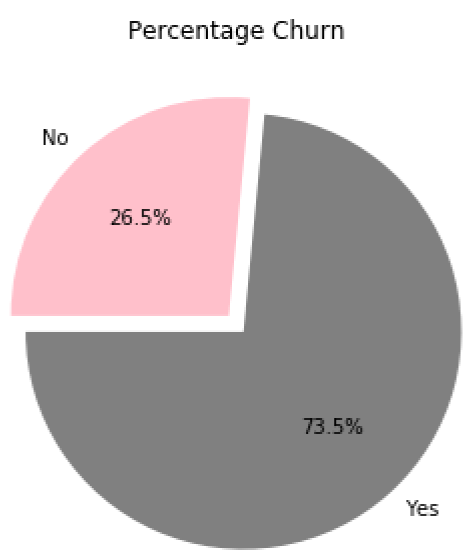
In [309]:

```
#plot data
from pylab import rcParams
import warnings
warnings.filterwarnings("ignore")

sizes = feature_churn['Churn_Yes'].value_counts(sort=True)
colors = ["grey","pink"]
rcParams['figure.figsize'] = 5,5

#Pie Chart
plt.pie(sizes, explode = (0.05,0.05),labels = ["Yes","No"], colors = colors, a
utopct = '%1.1f%%',startangle = 180)

plt.title('Percentage Churn')
plt.show()
```



Logistic Regression Model to test features (Baseline)

Model shows 80% accuracy in predicting outcomes of Churn based on inputs. Running optimzation statistical logistics regression model with X_feat = selected_feats_churn.loc[:,1:] X_train, X_test, Y_train, Y_test = train_test_split(X_feat,Y,test_size = 0.30, random_state = 101) import statsmodels.api as sm logit_model=sm.Logit(Y_train,X_train) result=logit_model.fit() print(result.summary2()) #we get the below summaryRemoving Month to Month as it is not statistically significant Optimization terminated successfully. Current function value: inf Iterations 8 Results: Logit == Model: Logit Pseudo R-squared: inf Dependent Variable: Churn_Yes AIC: inf Date: 2019-11-22 17:52 BIC: inf No. Observations: 4930 Log-Likelihood: -inf Df Model: 9 LL-Null: 0.0000 Df Residuals: 4920 LLR p-value: 1.0000 Converged: 1.0000 Scale: 1.0000 No. Iterations: 8.0000 -- Coef. Std.Err. z P>|z| [0.025 0.975] -- SeniorCitizen 0.2916 0.0982 2.9687 0.0030 0.0991 0.4841 Contract_Two year -1.2530 0.2057 -6.0911 0.0000 -1.6562 -0.8498 TotalCharges 0.0007 0.0001 9.6265 0.0000 0.0006 0.0008 tenure -0.0932 0.0064 -14.5685 0.0000 -0.1057 -0.0806 MonthlyCharges -0.0173 0.0023 -7.3935 0.0000 -0.0219 -0.0127 Contract_Month-to-month -0.0605 0.0964 -0.6272 0.5305 -0.2494 0.1285 OnlineSecurity_No 0.4384 0.0932 4.7031 0.0000 0.2557 0.6211 PaymentMethod_Electronic check 0.4555 0.0812 5.6073 0.0000 0.2963 0.6147 TechSupport_No 0.4018 0.0929 4.3242 0.0000 0.2197 0.5839 InternetService_Fiber optic 1.2088 0.1330 9.0912 0.0000 0.9482 1.4694

In [271]:
```
#model with selected features:
feat_lin = feature_churn[['Churn_Yes','SeniorCitizen','Contract_Two year', 'To
talCharges','tenure','MonthlyCharges','OnlineSecurity_No','PaymentMethod_Elect
ronic check','TechSupport_No','InternetService_Fiber optic']]
X_feat = feat_lin.iloc[:,1:]
X_train, X_test, Y_train, Y_test = train_test_split(X_feat,Y,test_size = 0.30,
random_state = 101)

import statsmodels.api as sm
logit_model=sm.Logit(Y_train,X_train)
result=logit_model.fit()
print(result.summary2())
#we get the below summary

#import 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)

#print accuracy
print(str(metrics.accuracy_score(Y_test, prediction_test)*100)+'%')
```

```
Optimization terminated successfully.
         Current function value: inf
         Iterations 8
                             Results: Logit
============================================================================
==
Model:                    Logit                  Pseudo R-squared:      inf
Dependent Variable:       Churn_Yes              AIC:                   inf
Date:                     2019-11-22 18:11       BIC:                   inf
No. Observations:         4930                   Log-Likelihood:        -inf
Df Model:                 8                      LL-Null:               0.00
00
Df Residuals:             4921                   LLR p-value:           1.00
00
Converged:                1.0000                 Scale:                 1.00
00
No. Iterations:           8.0000
----------------------------------------------------------------------------
--
                                Coef.  Std.Err.    z     P>|z|   [0.025  0.97
5]
----------------------------------------------------------------------------
--
SeniorCitizen                   0.2883   0.0981   2.9399 0.0033  0.0961  0.48
05
Contract_Two year              -1.2321   0.2032  -6.0640 0.0000 -1.6304 -0.83
39
TotalCharges                    0.0007   0.0001  10.3846 0.0000  0.0006  0.00
08
tenure                         -0.0938   0.0063 -14.8132 0.0000 -0.1062 -0.08
14
MonthlyCharges                 -0.0181   0.0020  -9.0806 0.0000 -0.0220 -0.01
42
OnlineSecurity_No               0.4323   0.0927   4.6616 0.0000  0.2505  0.61
40
PaymentMethod_Electronic check  0.4507   0.0809   5.5725 0.0000  0.2922  0.60
92
TechSupport_No                  0.3935   0.0920   4.2770 0.0000  0.2132  0.57
39
InternetService_Fiber optic     1.2233   0.1312   9.3271 0.0000  0.9662  1.48
04
============================================================================
==

80.88026502602933%
```

We will now compare two other popular methods: Decision Tree, and K-Nearest-Neighbor to gauge best model to predict

In [272]:
```
#Print weights ov variables
weights = pd.Series(model.coef_[0], index = X_feat.columns.values)
weights.sort_values(ascending = False)
weights.sort_values(ascending = True)
```

Out[272]:
```
Contract_Two year                  -0.696976
tenure                             -0.063308
TotalCharges                        0.000307
MonthlyCharges                      0.000496
SeniorCitizen                       0.329954
PaymentMethod_Electronic check      0.427774
OnlineSecurity_No                   0.433929
TechSupport_No                      0.436380
InternetService_Fiber optic         0.897562
dtype: float64
```

Exploring other Machine Learning Predictive Models

Using decision trees then k-nearest-neight

In [304]:
```
from sklearn import tree

model = tree.DecisionTreeClassifier(random_state=0, max_depth=5)


from sklearn import metrics

results = []
for i in range(1,10): # replicating model to get best average
    result = model.fit(X_train, Y_train)
    prediction_test = model.predict(X_test)
#print accuracy
    results.append(float(metrics.accuracy_score(Y_test, prediction_test)*100))

#print((results))
#another method to get accuracy:
#from sklearn.metrics import accuracy_score
print(str(sum((results))/len(results))+'%')
#accuracy_score(Y_test, prediction_test)
```

```
78.98722195929957%
```

title

Not as good as our logistics regression model, but did not hurt to check

In [275]:
```
from sklearn.neighbors import KNeighborsClassifier

score_knn = 0
neighborcount = 3
max_value = -1

while score_knn > max_value:
    model = KNeighborsClassifier(n_neighbors=neighborcount)
    result = model.fit(X_train, Y_train)
    prediction_test = model.predict(X_test)
    max_value = float(score_knn)
    score_knn = float(metrics.accuracy_score(Y_test, prediction_test))
    neighborcount +=1
print(str(max_value*100)+'% using '+str(neighborcount) + ' neighbors')
#print((results))
#another method to get accuracy:
#from sklearn.metrics import accuracy_score

#accuracy_score(Y_test, prediction_test)
```

```
76.99952673923332% using 8 neighbors
```

A little better than our decision tree model, but still not as good as our linear regression.

End of Case Study

Personal Website (https://technerdhelp.com)

In [ ]: