Tree-based ML and Feature Selection

This week, your assignment is:

- use our prepared churn data from week 2
- break our data into features and targets, and train and test sets
- use sklearn to fit a decision tree to the training data
  - plot the decision tree
  - change the max_depth of the decision tree to improve the model if needed (or tune it with a hyperparameter search)
- plot the correlations between features and targets
- use sklearn to fit a random forest model to predict churn from our dataset
  - plot the feature importances from the random forest
- choose some of the less-important features to remove from the model using feature importances and correlations and fit the random forest model to the new data
  - examine the feature importances after removing less important features
- write a short analysis of the results of your work

***Optional* advanced tasks:**

- use H2O to fit a random forest to our original, unmodified data (missing values and all)
  - you can decide if you want to break the data into train and test sets or not, but remember it's best to evaluate performance on a test or validation dataset
  - plot the H2O random forest's feature importances
- tune the random forest hyperparameters for the sklearn and/or H2O models
- use forward and/or backward selection with feature importances from a random forest model
- use recursive feature selection
- compare the various feature selection methods you tried and write a short summary

In [23]:
```
#use our prepared churn data from week 2
import pandas as pd
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
```

In [24]:
```
df = pd.read_csv('clean_churn_data.csv', index_col='Unnamed: 0')
df
```

Out[24]:

	customerID	tenure	PhoneService	Contract	PaymentMethod	MonthlyCharges	TotalCharges	Churn	monthly_total_chg_ratio
0	7590-VHVEG	1	0	12	1	29.85	29.85	0	1.000000
1	5575-GNVDE	34	1	1	2	56.95	1889.50	0	0.030140
2	3668-QPYBK	2	1	12	2	53.85	108.15	1	0.497920
3	7795-CFOCW	45	0	1	3	42.30	1840.75	0	0.022980
4	9237-HQITU	2	1	12	1	70.70	151.65	1	0.466205
...	...	...	...	...	...	...	...	...	...
7038	6840-RESVB	24	1	1	2	84.80	1990.50	0	0.042602
7039	2234-XADUH	72	1	1	4	103.20	7362.90	0	0.014016
7040	4801-JZAZL	11	0	12	1	29.60	346.45	0	0.085438
7041	8361-LTMKD	4	1	12	2	74.40	306.60	1	0.242661
7042	3186-AJIEK	66	1	2	3	105.65	6844.50	0	0.015436

7043 rows × 9 columns

In [25]:

```
#break our data into features and targets, and train and test sets
features = df.drop(['customerID', 'Churn'], axis=1)
print('Features')
print(features)
targets = df['Churn']
print('Targets')
print(targets)
```

```
Features
      tenure  PhoneService  Contract  PaymentMethod  MonthlyCharges  \
0          1             0        12              1           29.85
1         34             1         1              2           56.95
2          2             1        12              2           53.85
3         45             0         1              3           42.30
4          2             1        12              1           70.70
...      ...           ...       ...            ...             ...
7038      24             1         1              2           84.80
7039      72             1         1              4          103.20
7040      11             0        12              1           29.60
7041       4             1        12              2           74.40
7042      66             1         2              3          105.65

      TotalCharges  monthly_total_chg_ratio
0            29.85                 1.000000
```

```
1          1889.50                0.030140
2           108.15                0.497920
3          1840.75                0.022980
4           151.65                0.466205
...            ...                     ...
7038       1990.50                0.042602
7039       7362.90                0.014016
7040        346.45                0.085438
7041        306.60                0.242661
7042       6844.50                0.015436

[7043 rows x 7 columns]
Targets
0       0
1       0
2       1
3       0
4       1
       ..
7038    0
7039    0
7040    0
7041    1
7042    0
Name: Churn, Length: 7043, dtype: int64
```

In [27]:

```
x_train, x_test, y_train, y_test = train_test_split(features, targets, stratify=targets, random_state=42)
print("x_train")
print(x_train)
print("x_test")
print(x_test)
print("y_train")
print(y_train)
print("y_test")
print(y_test)
#default size is 25% test size
```

```
x_train
      tenure  PhoneService  Contract  PaymentMethod  MonthlyCharges  \
6661      72             0         2              4           53.65
4811       4             1        12              2           46.00
2193      56             1         1              2           21.20
1904      56             1        12              1           94.45
6667       9             1        12              1           79.55
...      ...           ...       ...            ...             ...
4250      63             1         1              4          104.50
1488       1             1        12              2           51.25
6303      71             1         2              1          109.25
2710      24             1         1              4           20.40
```

```
5639       6             1        12              2           20.65

      TotalCharges  monthly_total_chg_ratio
6661       3784.00                 0.014178
4811        193.60                 0.237603
2193       1238.65                 0.017115
1904       5124.60                 0.018431
6667        723.40                 0.109967
...            ...                      ...
4250       6590.80                 0.015855
1488         51.25                 1.000000
6303       7707.70                 0.014174
2710        482.80                 0.042254
5639        109.30                 0.188930

[5282 rows x 7 columns]
x_test
      tenure  PhoneService  Contract  PaymentMethod  MonthlyCharges  \
5909      52             1         1              2           80.20
3670      33             1        12              3           24.25
6220      10             0         2              4           53.70
5905       1             1        12              1           85.00
6435      52             0         2              2           50.20
...      ...           ...       ...            ...             ...
476       35             1        12              1           76.05
1607      13             1        12              3           89.05
6808      39             1         2              1          100.45
2962       3             0        12              2           31.00
3955      29             0        12              1           45.90

      TotalCharges  monthly_total_chg_ratio
5909       4297.60                 0.018662
3670        838.50                 0.028921
6220        521.00                 0.103071
5905         85.00                 1.000000
6435       2554.00                 0.019655
...            ...                      ...
476        2747.20                 0.027683
1607       1169.35                 0.076153
6808       3801.70                 0.026422
2962         95.05                 0.326144
3955       1332.40                 0.034449

[1761 rows x 7 columns]
y_train
6661    0
4811    1
2193    0
1904    1
6667    1
```

```
       ..
4250    0
1488    0
6303    0
2710    0
5639    0
Name: Churn, Length: 5282, dtype: int64
y_test
5909    0
3670    0
6220    0
5905    0
6435    0
       ..
476     0
1607    1
6808    0
2962    1
3955    0
Name: Churn, Length: 1761, dtype: int64
```

In [28]:

```
#use sklearn to fit a decision tree to the training data
##plot the decision tree
dt = DecisionTreeClassifier()
dt.fit(x_train, y_train)
print(dt.score(x_train, y_train))
print(dt.score(x_test, y_test))
```

```
0.993563044301401
0.7257240204429302
```

In [29]:

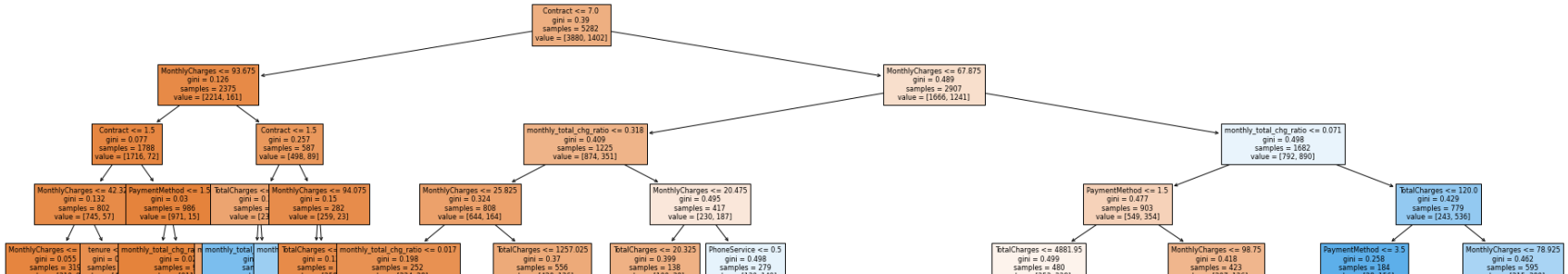
```
dt.get_depth()
```

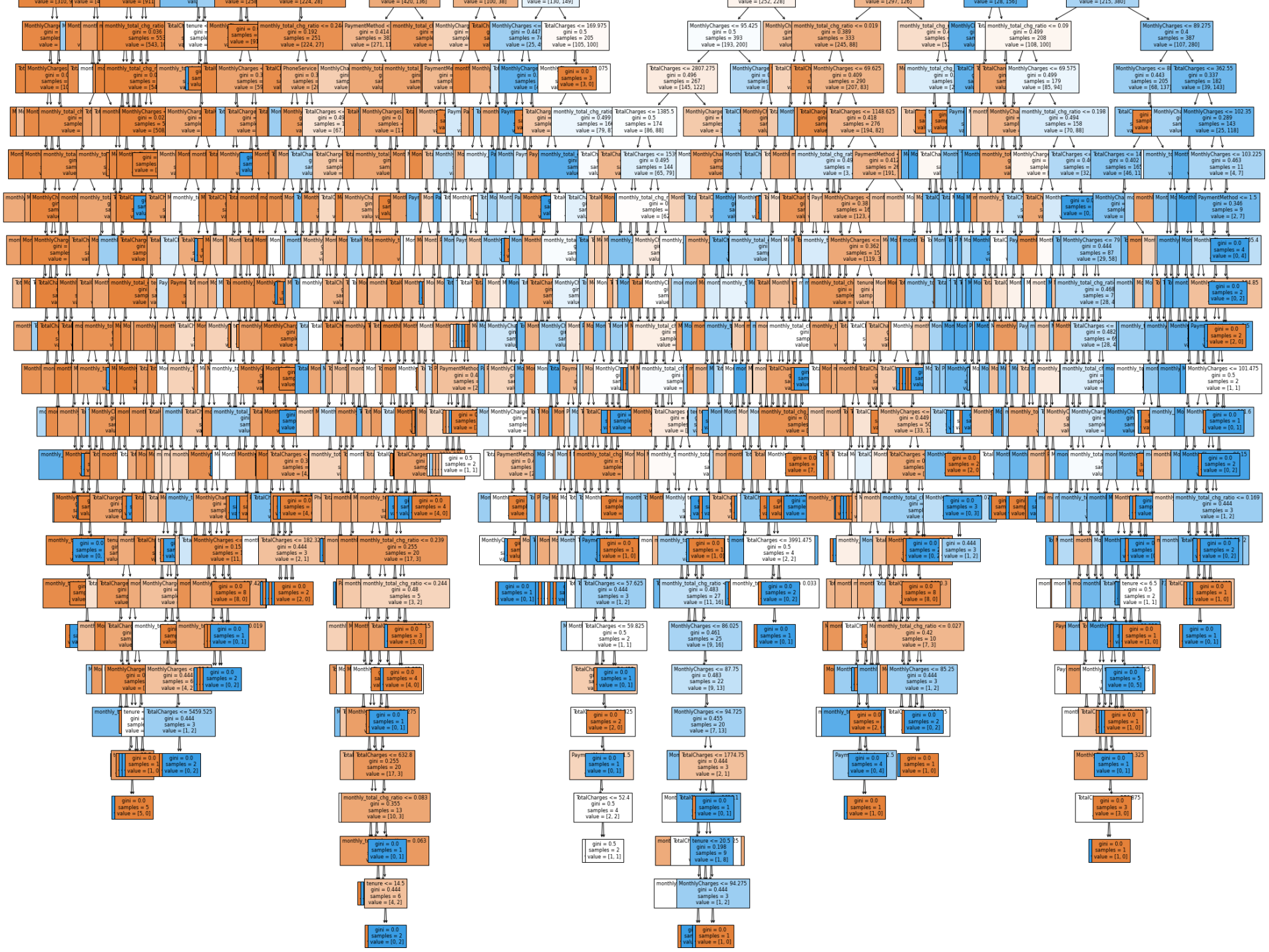
Out[29]:

```
26
```

In [30]:

```
f = plt.figure(figsize=(35, 35))
_ = plot_tree(dt, fontsize=8, feature_names=features.columns, filled=True)
```





In [31]:

```
##change the max_depth of the decision tree to improve the model if needed (or tune it with a hyperparameter search)
for x in range(3,20):
    print(f'\nCurrent Depth: {x}')
    dt = DecisionTreeClassifier(max_depth=x)
```

```
    dt.fit(x_train, y_train)
    print(dt.score(x_train, y_train))
    print(dt.score(x_test, y_test))
```

```
Current Depth: 3
0.7900416508898145
0.7796706416808632

Current Depth: 4
0.7942067398712609
0.7842135150482681

Current Depth: 5
0.7985611510791367
0.7779670641680864

Current Depth: 6
0.807080651268459
0.778534923339012

Current Depth: 7
0.8176826959485044
0.7768313458262351

Current Depth: 8
0.8309352517985612
0.7779670641680864

Current Depth: 9
0.8455130632336236
0.7751277683134583

Current Depth: 10
0.8612268080272624
0.760931289040318

Current Depth: 11
0.8756152972358955
0.7546848381601363

Current Depth: 12
0.8953048087845513
0.7495741056218058

Current Depth: 13
0.9113971980310488
0.7501419647927314

Current Depth: 14
0.9295721317682696
```

```
0.7444633730834753

Current Depth: 15
0.9396062097690269
0.7387847813742192

Current Depth: 16
0.9564558879212419
0.7359454855195912

Current Depth: 17
0.965921999242711
0.7314026121521863

Current Depth: 18
0.9744414994320333
0.7285633162975582

Current Depth: 19
0.9793638773191973
0.7251561612720046
```

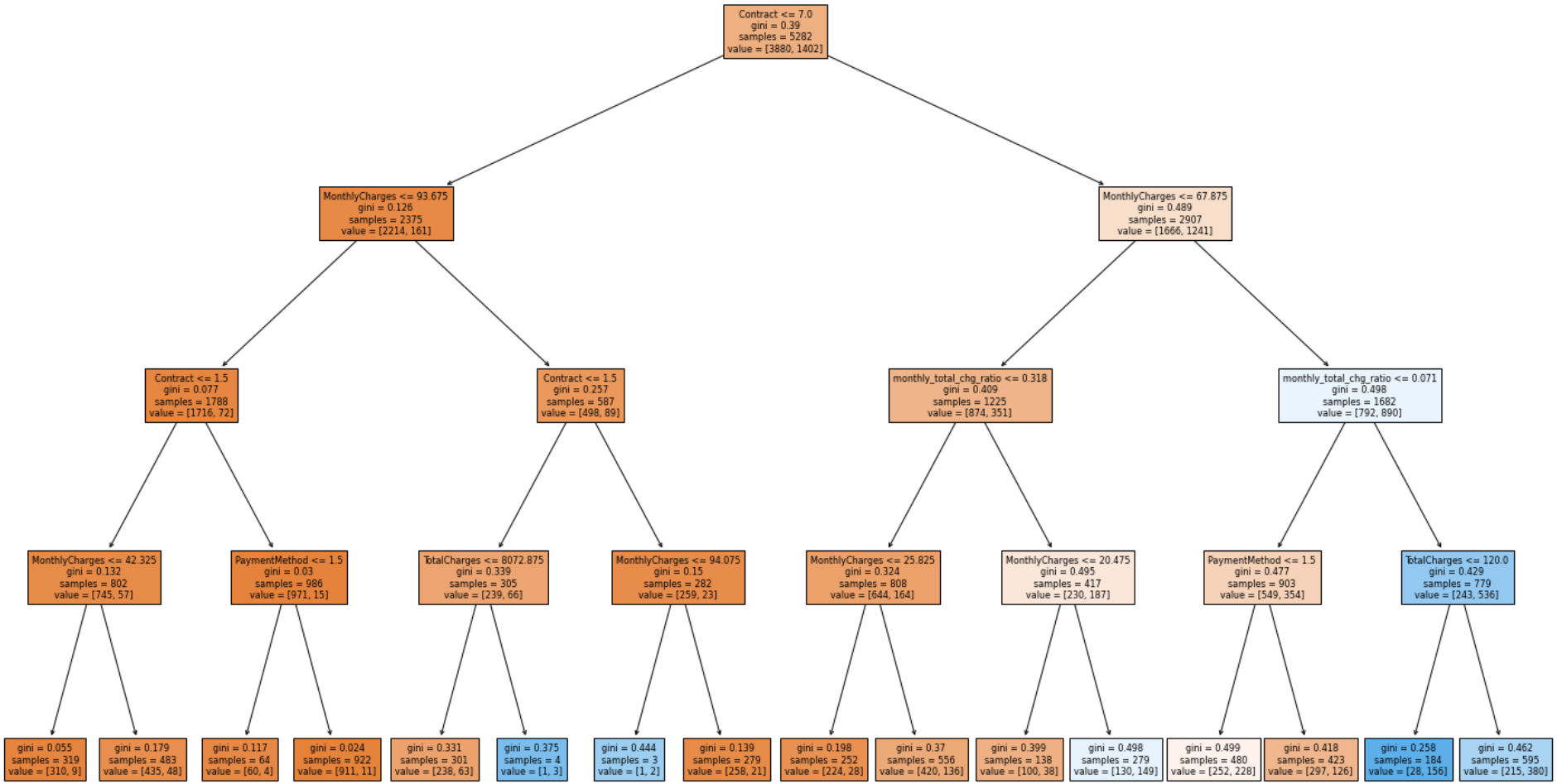
In [32]:

```
dt = DecisionTreeClassifier(max_depth=4)
dt.fit(x_train, y_train)
print(dt.score(x_train, y_train))
print(dt.score(x_test, y_test))
```

```
0.7942067398712609
0.7842135150482681
```

In [33]:

```
f = plt.figure(figsize=(25, 15))
_ = plot_tree(dt, fontsize=8, feature_names=features.columns, filled=True)
```

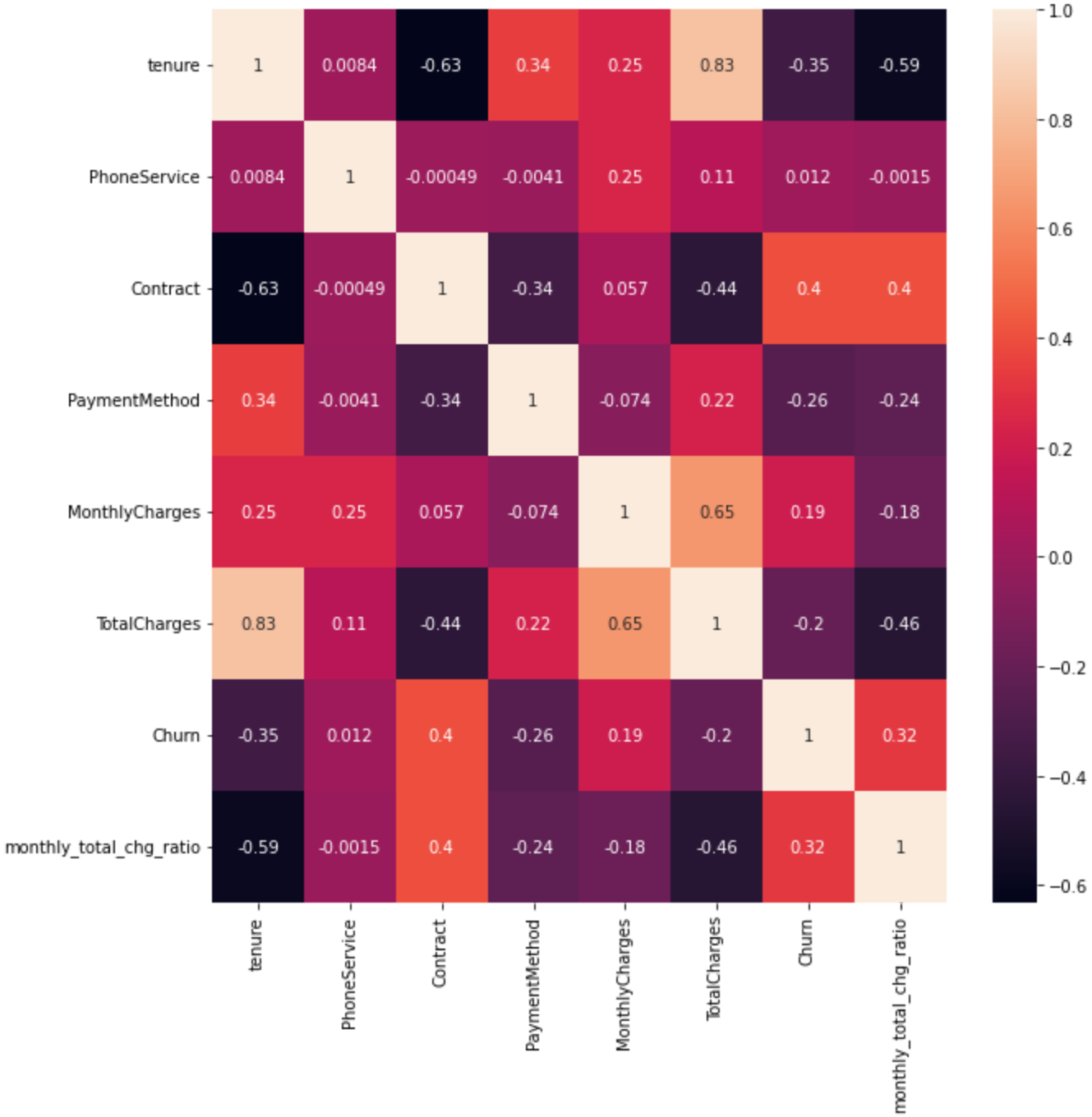


In [34]:

```
#plot the correlations between features and targets
import seaborn as sns
f = plt.figure(figsize=(10,10))
sns.heatmap(df.corr(), annot=True)
```

Out[34]:

```
<AxesSubplot:>
```



In [35]:

```
#use sklearn to fit a random forest model to predict churn from our dataset
from sklearn.ensemble import RandomForestClassifier

for x in range(2, 10):
    rfc = RandomForestClassifier(max_depth=x, random_state=42)
    rfc.fit(x_train, y_train)
```

```
    print(f'\nCurrent Max Depth: {x}')
    print(rfc.score(x_train, y_train))
    print(rfc.score(x_test, y_test))
```

```
Current Max Depth: 2
0.7798182506626278
0.7751277683134583

Current Max Depth: 3
0.7885270730783794
0.78137421919364

Current Max Depth: 4
0.7978038621734191
0.787052810902896

Current Max Depth: 5
0.807080651268459
0.7921635434412265

Current Max Depth: 6
0.812570995834911
0.7955706984667802

Current Max Depth: 7
0.8241196516471033
0.7961385576377058

Current Max Depth: 8
0.8386974630821659
0.7961385576377058

Current Max Depth: 9
0.8604695191215449
0.7950028392958546
```

In [36]:

```
#choosing max depth 7 because it's the most accurate and still not overfitted (too much)
rfc = RandomForestClassifier(max_depth=7, random_state=42)
rfc.fit(x_train, y_train)
print(rfc.score(x_train, y_train))
print(rfc.score(x_test, y_test))
```

```
0.8241196516471033
0.7961385576377058
```

In [37]:

```
for x in range(2, 8):
    rfc = RandomForestClassifier(max_depth=7, max_features=x, random_state=42)
    rfc.fit(x_train, y_train)
```

```
    print(f'\nCurrent Max Features: {x}')
    print(rfc.score(x_train, y_train))
    print(rfc.score(x_test, y_test))
```

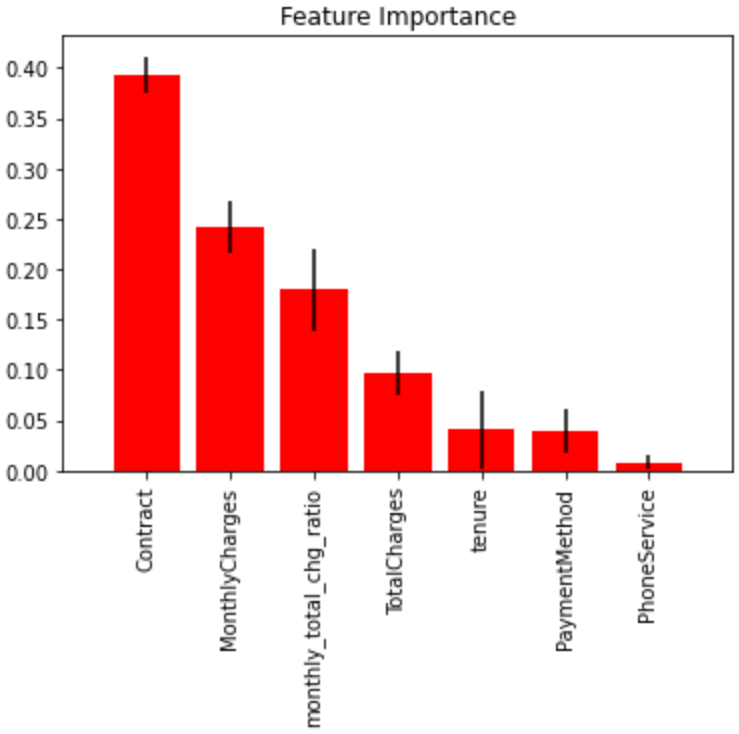
```
Current Max Features: 2
0.8241196516471033
0.7961385576377058

Current Max Features: 3
0.8301779628928436
0.7961385576377058

Current Max Features: 4
0.829420673987126
0.7927314026121521

Current Max Features: 5
0.8305566073457024
0.794434980124929

Current Max Features: 6
0.8318818629307081
0.7859170925610448

Current Max Features: 7
0.8324498296099963
0.7898921067575241
```

In [38]:

```
#so, default max features is the most accurate. still not overperforming the decision tree by a lot but at least by a little bit
##plot the feature importances from the random forest
from scikitplot.estimators import plot_feature_importances
plot_feature_importances(rfc, feature_names=features.columns, x_tick_rotation=90)
```

Out[38]:

```
<AxesSubplot:title={'center':'Feature Importance'}>
```



In [40]:

```
#choose some of the less-important features to remove from the model using feature importances and correlations and fit the random f
new_features = features.drop(['tenure', 'PaymentMethod', 'PhoneService'], axis=1)
x_train, x_test, y_train, y_test = train_test_split(new_features, targets, stratify=targets, random_state=42)
for x in range(2, 8):
    rfc = RandomForestClassifier(max_depth=x, random_state=42)
    rfc.fit(x_train, y_train)
    print(f'\nCurrent Max Depth: {x}')
    print(rfc.score(x_train, y_train))
    print(rfc.score(x_test, y_test))
```

```
Current Max Depth: 2
0.7872018174933737
0.7762634866553095

Current Max Depth: 3
0.7904202953426732
0.7773992049971608

Current Max Depth: 4
0.7966679288148428
0.7853492333901193

Current Max Depth: 5
0.8038621734191594
0.7859170925610448
```

```
Current Max Depth: 6
0.8097311624384703
0.787052810902896

Current Max Depth: 7
0.8218477849299508
0.7853492333901193
```

In [42]:

```
for x in range(2, 5):
    rfc = RandomForestClassifier(max_depth=6, max_features=x, random_state=42)
    rfc.fit(x_train, y_train)
    print(f'\nCurrent Max Features: {x}')
    print(rfc.score(x_train, y_train))
    print(rfc.score(x_test, y_test))
```

```
Current Max Features: 2
0.8097311624384703
0.787052810902896

Current Max Features: 3
0.8112457402499054
0.7853492333901193

Current Max Features: 4
0.8127603180613404
0.7853492333901193
```

In [43]:

```
# choosing max depth of 6 and max features as 2 because that leads to the highest test accuracy without being overfitted/underfitte
rfc = RandomForestClassifier(max_depth=6, max_features=2, random_state=42)
rfc.fit(x_train, y_train)
print(rfc.score(x_train, y_train))
print(rfc.score(x_test, y_test))
```

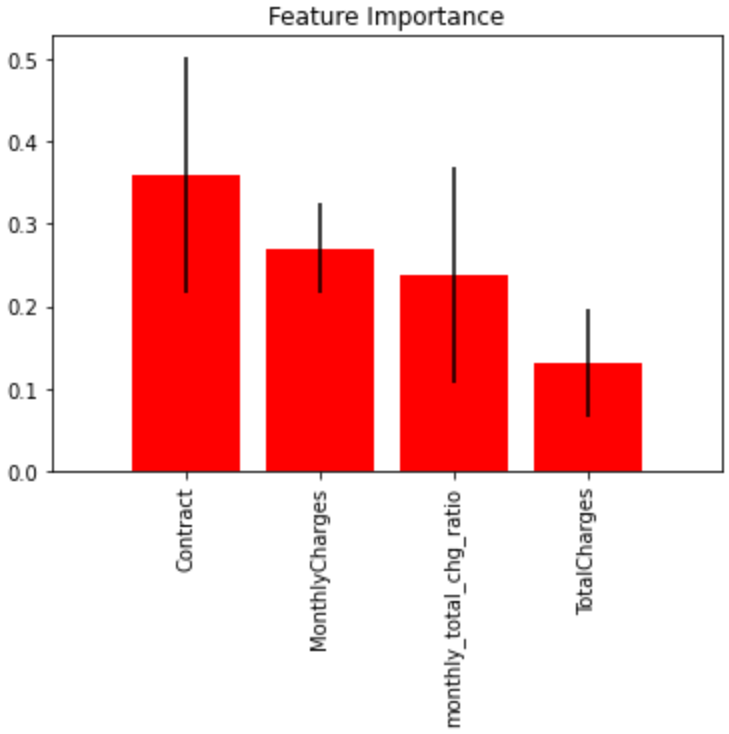
```
0.8097311624384703
0.787052810902896
```

In [44]:

```
##examine the feature importances after removing less important features
plot_feature_importances(rfc, feature_names=new_features.columns, x_tick_rotation=90)
```

Out[44]:

```
<AxesSubplot:title={'center':'Feature Importance'}>
```



Summary

Be sure to write a summary of your work and explain the results.

Analysis of Work

During the assignment above, I explored decision trees and feature importance/selection as well as correlation heatmaps. Below is a short list of the actions I performed as well an analysis of their results:

- I imported the clean_churn_data dataset and set the target as the churn, and the features as all the numerical columns (dropping 'Customer ID' as it is categorical).
- I created a train and test dataset based on the default train/test ratio of 25%.
- I fit the training data to a decision tree classifier.
  - The depth was 26 and the decision tree was terribly cluttered.
  - The training accuracy was 0.9936 and the test accuracy was 0.7257.
- Using a for-loop which iterates through max_depth, I optimized the max_depth of the decision tree.
  - The optimum max_depth was 4.
  - The new training accuracy was 0.7942 and the test accuracy was 0.7842. Much less over-fitted than before.

- I plotted the new decision tree (with new max_depth of 4)
- I plotted the pearson correlation heatmap to show correlations between all features and target.
  - 'Tenure', 'PaymentMethod', and 'PhoneService' all have negative correlations.
- I created a RandomForestClassifier, and used 2 for-loops to optimize the max_depth and max_features.
  - Optimal max_depth was 7 and optimal max_features was default.
  - New training accuracy was 0.8241 and new test accuracy was 0.7961. The RFC out-performed the decision tree just slightly.
- I plotted the feature importance chart. I then dropped the Tenure, PaymentMethod, and PhoneService features as they had a negative correlation. I then used the same 2 for-loops to optimize the max_depth and max_features of the new dataset with the dropped features.
  - Optimal max_depth was 6 and optimal max_features was 2.
  - The new trainin accuracy was 0.8097 and the new test accuracy was 0.7871.
- I re-plotted the feature importance, showing the new dataset with the dropped features.

Thank you! Please let me know if you have any questions.

All the best, Jeremy

In [ ]: