Week4_Assignment

February 12, 2024

[1]:
```
import pandas as pd
import h2o
from h2o.estimators import H2ORandomForestEstimator
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.tree import DecisionTreeClassifier, export_text
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
```

0.1 Load data

[2]:
```
df = pd.read_csv("preped_churn_data.csv")

df.sample(10)
```

[2]:
```
      tenure PhoneService        Contract              PaymentMethod  \
1198      42          Yes        Two year  Bank transfer (automatic)
5028      72          Yes        Two year           Electronic check
1532      14          Yes  Month-to-month    Credit card (automatic)
83        42          Yes  Month-to-month  Bank transfer (automatic)
4003      38          Yes        Two year               Mailed check
1681      72          Yes        Two year    Credit card (automatic)
879       33          Yes  Month-to-month  Bank transfer (automatic)
2921       9          Yes  Month-to-month           Electronic check
5185      50          Yes        One year    Credit card (automatic)
1257      45           No        One year           Electronic check

      MonthlyCharges  TotalCharges Churn  \
1198           20.75        844.45    No
5028          109.90       7624.20    No
1532           19.60        300.40    No
83            103.80       4327.50    No
4003           20.30        743.05    No
1681           25.00       1849.20    No
879            54.65       1665.20    No
2921           95.50        829.10   Yes
5185           70.80       3478.15    No
```

```
1257           34.20       1596.60    No

      TotalCharges_to_MonthlyCharges_ratio  customerID
1198                             40.696386        1199
5028                             69.373976        5029
1532                             15.326531        1533
83                               41.690751          84
4003                             36.603448        4004
1681                             73.968000        1682
879                              30.470265         880
2921                              8.681675        2922
5185                             49.126412        5186
1257                             46.684211        1258
```

[3]:
```python
df['Churn'] = df['Churn'].map({'Yes': 1, 'No': 0})

df['PhoneService'] = df['PhoneService'].map({'Yes': 1, 'No': 0})
df
```

[3]:
```
      tenure  PhoneService        Contract              PaymentMethod  \
0          1             0  Month-to-month           Electronic check
1         34             1        One year               Mailed check
2          2             1  Month-to-month               Mailed check
3         45             0        One year  Bank transfer (automatic)
4          2             1  Month-to-month           Electronic check
…      …             …             …                          …
7038      24             1        One year               Mailed check
7039      72             1        One year    Credit card (automatic)
7040      11             0  Month-to-month           Electronic check
7041       4             1  Month-to-month               Mailed check
7042      66             1        Two year  Bank transfer (automatic)

      MonthlyCharges  TotalCharges  Churn  \
0              29.85         29.85      0
1              56.95       1889.50      0
2              53.85        108.15      1
3              42.30       1840.75      0
4              70.70        151.65      1
…               …            …    …
7038           84.80       1990.50      0
7039          103.20       7362.90      0
7040           29.60        346.45      0
7041           74.40        306.60      1
7042          105.65       6844.50      0

      TotalCharges_to_MonthlyCharges_ratio  customerID
0                                 1.000000           1
```

```
1                                33.178227        2
2                                 2.008357        3
3                                43.516548        4
4                                 2.144979        5
…                                       …         …
7038                             23.472877     7039
7039                             71.345930     7040
7040                             11.704392     7041
7041                              4.120968     7042
7042                             64.784666     7043

[7043 rows x 9 columns]
```

[4]:

```python
PM_dummies = pd.get_dummies(df['PaymentMethod'], prefix='PaymentMethod')
C_dummies = pd.get_dummies(df['Contract'], prefix='Contract')

df = pd.concat([df, PM_dummies, C_dummies], axis=1)

df = df.loc[:, ~df.columns.duplicated()]

df.head(5)
```

[4]:

```
   tenure  PhoneService        Contract              PaymentMethod  \
0       1             0  Month-to-month           Electronic check
1      34             1        One year               Mailed check
2       2             1  Month-to-month               Mailed check
3      45             0        One year  Bank transfer (automatic)
4       2             1  Month-to-month           Electronic check

   MonthlyCharges  TotalCharges  Churn  TotalCharges_to_MonthlyCharges_ratio  \
0           29.85         29.85      0                              1.000000
1           56.95       1889.50      0                             33.178227
2           53.85        108.15      1                              2.008357
3           42.30       1840.75      0                             43.516548
4           70.70        151.65      1                              2.144979

   customerID  PaymentMethod_Bank transfer (automatic)  \
0           1                                    False
1           2                                    False
2           3                                    False
3           4                                     True
4           5                                    False

   PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
0                                  False                            True
1                                  False                           False
2                                  False                           False
```

```
3                                  False                           False
4                                  False                            True

   PaymentMethod_Mailed check  Contract_Month-to-month  Contract_One year  \
0                       False                     True              False
1                        True                    False               True
2                        True                     True              False
3                       False                    False               True
4                       False                     True              False

   Contract_Two year
0              False
1              False
2              False
3              False
4              False
```

[5]:
```
dummies = ['Contract_Month-to-month', 'Contract_One year', 'Contract_Two year',␣
 ↪'PaymentMethod_Bank transfer (automatic)', 'PaymentMethod_Electronic check',␣
 ↪'PaymentMethod_Mailed check', 'PaymentMethod_Credit card (automatic)']

for column in dummies:
    df[column] = pd.factorize(df[column])[0]

df.sample(5)
```

[5]:
```
      tenure  PhoneService        Contract              PaymentMethod  \
5246       2             1  Month-to-month           Electronic check
3896      38             1        One year               Mailed check
5493       6             1  Month-to-month           Electronic check
2498      27             1  Month-to-month           Electronic check
3552      68             1        Two year  Bank transfer (automatic)

      MonthlyCharges  TotalCharges  Churn  \
5246           79.75        164.50      1
3896           20.30        749.35      0
5493           84.35        474.90      1
2498           53.80       1389.85      0
3552          102.10       7149.35      0

      TotalCharges_to_MonthlyCharges_ratio  customerID  \
5246                              2.062696        5247
3896                             36.913793        3897
5493                              5.630113        5494
2498                             25.833643        2499
3552                             70.023017        3553
```

```
      PaymentMethod_Bank transfer (automatic)  \
5246                                        0
3896                                        0
5493                                        0
2498                                        0
3552                                        1

      PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
5246                                      0                               0
3896                                      0                               1
5493                                      0                               0
2498                                      0                               0
3552                                      0                               1

      PaymentMethod_Mailed check  Contract_Month-to-month  Contract_One year  \
5246                           0                        0                  0
3896                           1                        1                  1
5493                           0                        0                  0
2498                           0                        0                  0
3552                           0                        1                  0

      Contract_Two year
5246                  0
3896                  0
5493                  0
2498                  0
3552                  1
```

[6]:
```python
df = df.drop(['PaymentMethod', 'Contract', 'customerID'], axis=1)
df
```

[6]:
```
      tenure  PhoneService  MonthlyCharges  TotalCharges  Churn  \
0          1             0           29.85         29.85      0
1         34             1           56.95       1889.50      0
2          2             1           53.85        108.15      1
3         45             0           42.30       1840.75      0
4          2             1           70.70        151.65      1
…        …            …              …            …     …
7038      24             1           84.80       1990.50      0
7039      72             1          103.20       7362.90      0
7040      11             0           29.60        346.45      0
7041       4             1           74.40        306.60      1
7042      66             1          105.65       6844.50      0

      TotalCharges_to_MonthlyCharges_ratio  \
0                                 1.000000
1                                33.178227
```

```
2                                2.008357
3                               43.516548
4                                2.144979
…                                     …
7038                            23.472877
7039                            71.345930
7040                            11.704392
7041                             4.120968
7042                            64.784666

      PaymentMethod_Bank transfer (automatic)  \
0                                           0
1                                           0
2                                           0
3                                           1
4                                           0
…                                        …
7038                                        0
7039                                        0
7040                                        0
7041                                        0
7042                                        1

      PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
0                                         0                               0
1                                         0                               1
2                                         0                               1
3                                         0                               1
4                                         0                               0
…                                      …                            …
7038                                      0                               1
7039                                      1                               1
7040                                      0                               0
7041                                      0                               1
7042                                      0                               1

      PaymentMethod_Mailed check  Contract_Month-to-month  Contract_One year  \
0                              0                        0                  0
1                              1                        1                  1
2                              1                        0                  0
3                              0                        1                  1
4                              0                        0                  0
…                           …                     …                …
7038                           1                        1                  1
7039                           0                        1                  1
7040                           0                        0                  0
7041                           1                        0                  0
```

```
7042                          0                        1                  0

      Contract_Two year
0                     0
1                     0
2                     0
3                     0
4                     0
…                 …
7038                  0
7039                  0
7040                  0
7041                  0
7042                  1

[7043 rows x 13 columns]
```

[7]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 13 columns):
 #   Column                                   Non-Null Count  Dtype
---  ------                                   --------------  -----
 0   tenure                                   7043 non-null   int64
 1   PhoneService                             7043 non-null   int64
 2   MonthlyCharges                           7043 non-null   float64
 3   TotalCharges                             7043 non-null   float64
 4   Churn                                    7043 non-null   int64
 5   TotalCharges_to_MonthlyCharges_ratio     7043 non-null   float64
 6   PaymentMethod_Bank transfer (automatic)  7043 non-null   int64
 7   PaymentMethod_Credit card (automatic)    7043 non-null   int64
 8   PaymentMethod_Electronic check           7043 non-null   int64
 9   PaymentMethod_Mailed check               7043 non-null   int64
 10  Contract_Month-to-month                  7043 non-null   int64
 11  Contract_One year                        7043 non-null   int64
 12  Contract_Two year                        7043 non-null   int64
dtypes: float64(3), int64(10)
memory usage: 715.4 KB
```

[8]:
```python
df.isna().sum()
```

[8]:
```
tenure                                     0
PhoneService                               0
MonthlyCharges                             0
TotalCharges                               0
Churn                                      0
TotalCharges_to_MonthlyCharges_ratio       0
```

```
PaymentMethod_Bank transfer (automatic)    0
PaymentMethod_Credit card (automatic)      0
PaymentMethod_Electronic check             0
PaymentMethod_Mailed check                 0
Contract_Month-to-month                    0
Contract_One year                          0
Contract_Two year                          0
dtype: int64
```

0.2 Split into features and targets

[9]:
```python
X = df.drop('Churn', axis=1)
y = df['Churn']
```

0.3 Split nto training and test sets

[10]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42)
```

0.4 Fit and plot the DT

[11]:
```python
dt_model = DecisionTreeClassifier(max_depth=5)
dt_model.fit(X_train, y_train)
```

[11]:
```
DecisionTreeClassifier(max_depth=5)
```

[12]:
```python
tr= export_text(dt_model, feature_names=list(X.columns))
print(tr)
```

```
|--- Contract_Month-to-month <= 0.50
|   |--- MonthlyCharges <= 68.62
|   |   |--- TotalCharges_to_MonthlyCharges_ratio <= 3.75
|   |   |   |--- MonthlyCharges <= 20.88
|   |   |   |   |--- TotalCharges <= 20.57
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges >  20.57
|   |   |   |   |   |--- class: 0
|   |   |   |--- MonthlyCharges >  20.88
|   |   |   |   |--- PaymentMethod_Electronic check <= 0.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- PaymentMethod_Electronic check >  0.50
|   |   |   |   |   |--- class: 0
|   |   |--- TotalCharges_to_MonthlyCharges_ratio >  3.75
|   |   |   |--- PhoneService <= 0.50
|   |   |   |   |--- TotalCharges <= 330.30
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges >  330.30
|   |   |   |   |   |--- class: 0
```

```
|   |   |   |--- PhoneService >  0.50
|   |   |   |   |--- TotalCharges_to_MonthlyCharges_ratio <= 17.79
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges_to_MonthlyCharges_ratio >  17.79
|   |   |   |   |   |--- class: 0
|   |--- MonthlyCharges >  68.62
|   |   |--- TotalCharges_to_MonthlyCharges_ratio <= 13.16
|   |   |   |--- TotalCharges <= 120.00
|   |   |   |   |--- MonthlyCharges <= 69.88
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- MonthlyCharges >  69.88
|   |   |   |   |   |--- class: 1
|   |   |   |--- TotalCharges >  120.00
|   |   |   |   |--- MonthlyCharges <= 90.78
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- MonthlyCharges >  90.78
|   |   |   |   |   |--- class: 1
|   |   |--- TotalCharges_to_MonthlyCharges_ratio >  13.16
|   |   |   |--- PaymentMethod_Electronic check <= 0.50
|   |   |   |   |--- tenure <= 55.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- tenure >  55.50
|   |   |   |   |   |--- class: 0
|   |   |   |--- PaymentMethod_Electronic check >  0.50
|   |   |   |   |--- TotalCharges_to_MonthlyCharges_ratio <= 53.08
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges_to_MonthlyCharges_ratio >  53.08
|   |   |   |   |   |--- class: 0
|--- Contract_Month-to-month >  0.50
|   |--- MonthlyCharges <= 93.67
|   |   |--- Contract_One year <= 0.50
|   |   |   |--- MonthlyCharges <= 79.72
|   |   |   |   |--- MonthlyCharges <= 79.67
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges >  79.67
|   |   |   |   |   |--- class: 0
|   |   |   |--- MonthlyCharges >  79.72
|   |   |   |   |--- class: 0
|   |   |--- Contract_One year >  0.50
|   |   |   |--- MonthlyCharges <= 41.38
|   |   |   |   |--- TotalCharges <= 37.08
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges >  37.08
|   |   |   |   |   |--- class: 0
|   |   |   |--- MonthlyCharges >  41.38
|   |   |   |   |--- MonthlyCharges <= 42.70
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- MonthlyCharges >  42.70
```

```
|   |   |   |   |   |--- class: 0
|   |--- MonthlyCharges >  93.67
|   |   |--- TotalCharges_to_MonthlyCharges_ratio <= 70.35
|   |   |   |--- Contract_One year <= 0.50
|   |   |   |   |--- MonthlyCharges <= 94.22
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- MonthlyCharges >  94.22
|   |   |   |   |   |--- class: 0
|   |   |   |--- Contract_One year >  0.50
|   |   |   |   |--- TotalCharges <= 7523.15
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges >  7523.15
|   |   |   |   |   |--- class: 1
|   |   |--- TotalCharges_to_MonthlyCharges_ratio >  70.35
|   |   |   |--- TotalCharges <= 8639.60
|   |   |   |   |--- TotalCharges_to_MonthlyCharges_ratio <= 74.17
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges_to_MonthlyCharges_ratio >  74.17
|   |   |   |   |   |--- class: 0
|   |   |   |--- TotalCharges >  8639.60
|   |   |   |   |--- class: 1
```

0.5 Hyperparameter tuning

[13]:
```
param_grid = {'max_depth': [3, 5, 7, 10]}
dt_model = DecisionTreeClassifier()
grid_search = GridSearchCV(dt_model, param_grid, cv=5)
grid_search.fit(X_train, y_train)
```

[13]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'max_depth': [3, 5, 7, 10]})
```

0.6 Bests max_depth

[14]:
```
best_max_depth = grid_search.best_params_['max_depth']
best_max_depth
```

[14]:
```
3
```

0.7 Fit and plot DT with best hyperparameters

[15]:
```
dt_model_tuned = DecisionTreeClassifier(max_depth=best_max_depth)
dt_model_tuned.fit(X_train, y_train)
```

[15]:
```
DecisionTreeClassifier(max_depth=3)
```

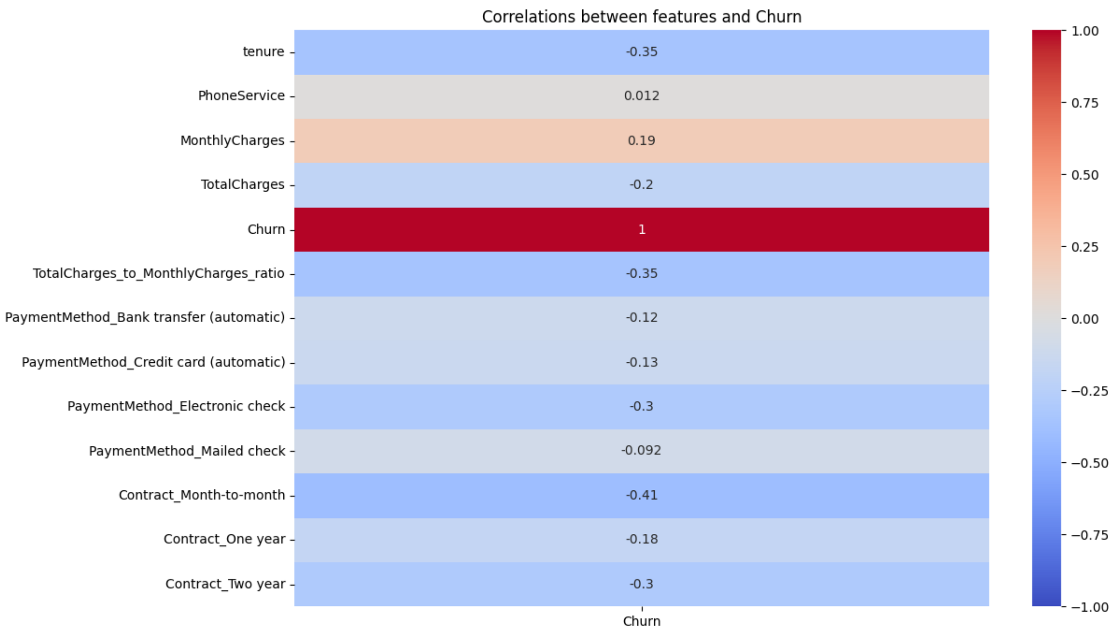
[16]:
```
tr_tuned = export_text(dt_model_tuned, feature_names=list(X.columns))
print(tr_tuned)
```

```
|--- Contract_Month-to-month <= 0.50
|   |--- MonthlyCharges <= 68.62
|   |   |--- TotalCharges_to_MonthlyCharges_ratio <= 3.75
|   |   |   |--- class: 0
|   |   |--- TotalCharges_to_MonthlyCharges_ratio >  3.75
|   |   |   |--- class: 0
|   |--- MonthlyCharges >  68.62
|   |   |--- TotalCharges_to_MonthlyCharges_ratio <= 13.16
|   |   |   |--- class: 1
|   |   |--- TotalCharges_to_MonthlyCharges_ratio >  13.16
|   |   |   |--- class: 0
|--- Contract_Month-to-month >  0.50
|   |--- MonthlyCharges <= 93.67
|   |   |--- Contract_Two year <= 0.50
|   |   |   |--- class: 0
|   |   |--- Contract_Two year >  0.50
|   |   |   |--- class: 0
|   |--- MonthlyCharges >  93.67
|   |   |--- TotalCharges_to_MonthlyCharges_ratio <= 70.35
|   |   |   |--- class: 0
|   |   |--- TotalCharges_to_MonthlyCharges_ratio >  70.35
|   |   |   |--- class: 0
```

After hyperparameter tuning, the decision tree with the best_max_depth of 3 provides a more detailed view of potential predictors for customer churn. The tree structure indicates that customers with shorter month-to-month contract durations, lower monthly charges, and specific ratios of charges are more likely to churn (class: 1). Additionally, the tree introduces new conditions, such as the tenure-related features, total charges, and payment methods, providing a more granular understanding of customer behavior.

0.8 Correlataions between features and targets

[17]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr()[['Churn']], annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title("Correlations between features and Churn")
plt.show()
```



0.9 Using h2o cluster

[ ]:
```
h2o.init()
```

[19]:
```
hf = h2o.H2OFrame(df)
```

```
Parse progress:
|                                          | (done) 100%
```

[20]:
```
train, test = hf.split_frame(ratios=[0.8], seed=42)
```

0.10 Fit h2o Random Forest

[21]:
```
rf_h2o = H2ORandomForestEstimator(seed=42)
rf_h2o.train(x=hf.columns[:-1], y="Churn", training_frame=train)
```

```
drf Model Build progress: |

/home/sensei/.local/lib/python3.11/site-
packages/h2o/estimators/estimator_base.py:192: RuntimeWarning: We have detected
that your response column has only 2 unique values (0/1). If you wish to train a
binary model instead of a regression model, convert your target column to
categorical before training.
  warnings.warn(mesg["message"], RuntimeWarning)
                                   | (done) 100%
```

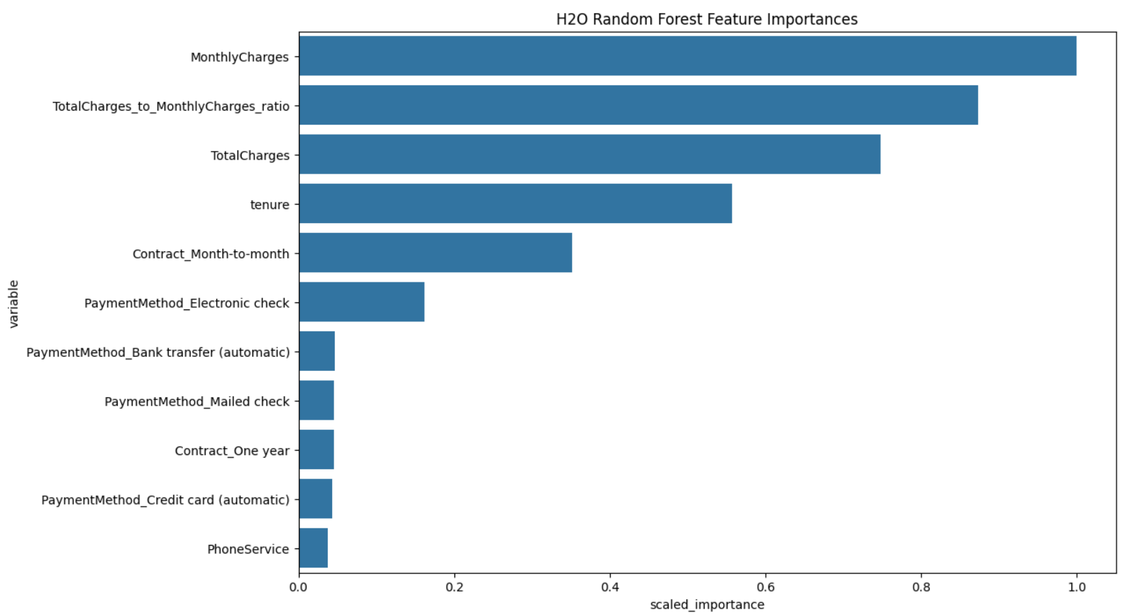
[21]:
```
Model Details
=============
H2ORandomForestEstimator : Distributed Random Forest
Model Key: DRF_model_python_1707690266499_3


Model Summary:
    number_of_trees    number_of_internal_trees    model_size_in_bytes
min_depth    max_depth    mean_depth    min_leaves    max_leaves    mean_leaves
--  -----------------  --------------------------  ---------------------
-----------  -----------  ------------  ------------  ------------
-------------
    50                 50                          559013                 20
20           20            677           949           884.36

ModelMetricsRegression: drf
** Reported on train data. **

MSE: 0.15774412810130986
RMSE: 0.3971701500633071
MAE: 0.2686530996248829
RMSLE: 0.2795712145057003
Mean Residual Deviance: 0.15774412810130986

Scoring History:
     timestamp            duration    number_of_trees    training_rmse
training_mae         training_deviance
---  -------------------  ----------  -----------------  -------------------
-------------------  -------------------
     2024-02-12 02:10:03  0.010 sec   0.0                nan
nan                  nan
     2024-02-12 02:10:03  0.070 sec   1.0                0.5154630062894613
0.27579260292488367  0.2657021108529692
     2024-02-12 02:10:03  0.091 sec   2.0                0.4979091988363233
0.268514992629594    0.2479135702858293
     2024-02-12 02:10:03  0.113 sec   3.0                0.48250070455236443
0.26628261689312005  0.23280692989352805
     2024-02-12 02:10:03  0.135 sec   4.0                0.4782295541855733
0.2703415020837108   0.22870350649653218
     2024-02-12 02:10:03  0.156 sec   5.0                0.4659625520665139
0.26851994370601157  0.21712109992833867
     2024-02-12 02:10:03  0.178 sec   6.0                0.4575545957450176
0.2688221898486882   0.2093562080873865
     2024-02-12 02:10:03  0.202 sec   7.0                0.4479999497764946
0.267086238085245    0.20070395499974167
     2024-02-12 02:10:03  0.240 sec   8.0                0.44251409827928573
0.267469200856907    0.19581872717592935
```

```
     2024-02-12 02:10:04  1.421 sec   9.0                 0.4381472979392279
0.267797891914376    0.19197305469144654
---  ---                   ---         ---                 ---
---                  ---
     2024-02-12 02:10:06  2.708 sec   41.0                0.39935892278663687
0.268884164293669    0.159487549209303
     2024-02-12 02:10:06  2.751 sec   42.0                0.3992773836700508
0.2689012220193489   0.15942242911040092
     2024-02-12 02:10:06  2.796 sec   43.0                0.3988916311520161
0.2688496596505218   0.15911453340311607
     2024-02-12 02:10:06  2.860 sec   44.0                0.3984211642320937
0.2687127707105981   0.158739424108057
     2024-02-12 02:10:06  2.912 sec   45.0                0.3980857181538183
0.2685123453935268   0.15847223899804128
     2024-02-12 02:10:06  2.963 sec   46.0                0.3981268443054598
0.26873277255738004  0.15850498415662384
     2024-02-12 02:10:06  3.018 sec   47.0                0.39801876186829677
0.2687787162816915   0.1584189347991719
     2024-02-12 02:10:06  3.058 sec   48.0                0.39757195988590244
0.2686759987031235   0.15806346328751764
     2024-02-12 02:10:06  3.104 sec   49.0                0.3974260781670253
0.26876258939016195  0.15794748760722252
     2024-02-12 02:10:06  3.154 sec   50.0                0.3971701500633071
0.2686530996248829   0.15774412810130986
[51 rows x 7 columns]


Variable Importances:
variable                                 relative_importance
scaled_importance    percentage
---------------------------------------  ---------------------
-------------------  ------------
MonthlyCharges                           8918.6                 1
0.255744
TotalCharges_to_MonthlyCharges_ratio     7784.55                0.872845
0.223225
TotalCharges                             6669.52                0.747821
0.191251
tenure                                   4964.1                 0.5566
0.142347
Contract_Month-to-month                  3137.84                0.351831
0.0899786
PaymentMethod_Electronic check           1445.72                0.162102
0.0414567
PaymentMethod_Bank transfer (automatic)  416.238                0.0466707
0.0119358
PaymentMethod_Mailed check               408.443                0.0457967
```

```
0.0117122
Contract_One year                        408.276                0.0457781
0.0117075
PaymentMethod_Credit card (automatic)    384.786                0.0431442
0.0110339
PhoneService                             335.074                0.0375703
0.00960837

[tips]
Use `model.explain()` to inspect the model.
--
Use `h2o.display.toggle_user_tips()` to switch on/off this section.
```

0.11 Plot h2o RF feature importances

[22]:
```python
plt.figure(figsize=(12, 8))
sns.barplot(x=rf_h2o.varimp(use_pandas=True)['scaled_importance'], y=rf_h2o.
 ↪varimp(use_pandas=True)['variable'])
plt.title("H2O Random Forest Feature Importances")
plt.show()
```



0.12 Hyperparameter tuning for h2o RF

[26]:
```python
hyper_params = {'ntrees': [50, 100, 200],'max_depth': [3, 5, 10, 20]}

search_criteria = {'strategy': "Cartesian"}
```

```
grid = h2o.grid.H2OGridSearch(model=H2ORandomForestEstimator,␣
 ↪grid_id='rf_grid', hyper_params=hyper_params,␣
 ↪search_criteria=search_criteria)

grid.train(x=hf.columns[:-1], y="Churn", training_frame=train)
```

```
drf Grid Build progress:
|                              | (done) 100%
```

[26]:

```
Hyper-Parameter Search Summary: ordered by increasing residual_deviance
     max_depth    ntrees    model_ids          residual_deviance
---  -----------  --------  ----------------  --------------------
     5            50.0      rf_grid_model_10  0.13781488588206756
     5            200.0     rf_grid_model_7   0.13783212656493118
     5            50.0      rf_grid_model_1   0.13791159722672194
     5            200.0     rf_grid_model_16  0.13801074899227886
     5            100.0     rf_grid_model_13  0.13807089860267113
     5            100.0     rf_grid_model_4   0.13814173740244173
     5            50.0      rf_grid_model_22  0.13846608179177328
     5            100.0     rf_grid_model_25  0.13847013754094648
     5            200.0     rf_grid_model_28  0.13863757176144811
     10           200.0     rf_grid_model_8   0.1401909249657123
---  ---          ---       ---               ---
     20           200.0     rf_grid_model_9   0.148251141151126
     20           100.0     rf_grid_model_6   0.15147812594614404
     20           200.0     rf_grid_model_30  0.15414500129118827
     20           50.0      rf_grid_model_3   0.15418989928987115
     20           200.0     rf_grid_model_18  0.1556643356409992
     20           100.0     rf_grid_model_27  0.15575871851537962
     20           100.0     rf_grid_model_27  0.15575871851537962
     20           50.0      rf_grid_model_24  0.15718932482060755
     20           100.0     rf_grid_model_15  0.15720762584792694
     20           50.0      rf_grid_model_12  0.15849556898288003
[33 rows x 5 columns]
```

0.13 Best hyperparameter

[27]:

```
best_rf_h2o = grid.models[0]
best_rf_h2o
```

[27]:

```
Model Details
=============
H2ORandomForestEstimator : Distributed Random Forest
Model Key: rf_grid_model_10
```

```
Model Summary:
    number_of_trees    number_of_internal_trees    model_size_in_bytes
min_depth    max_depth    mean_depth    min_leaves    max_leaves    mean_leaves
--  -----------------  -------------------------  ---------------------
-----------  -----------  ------------  ------------  ------------
-------------
    50                 50                          22563                  5
5            5             29            32            31.24

ModelMetricsRegression: drf
** Reported on train data. **

MSE: 0.13781488588206756
RMSE: 0.3712342735821513
MAE: 0.2788963132837725
RMSLE: 0.2602743165199784
Mean Residual Deviance: 0.13781488588206756

Scoring History:
     timestamp            duration    number_of_trees    training_rmse
training_mae         training_deviance
---  -------------------  ----------  -----------------  -------------------
-------------------  -------------------
     2024-02-12 01:31:57  0.050 sec   0.0                nan
nan                  nan
     2024-02-12 01:31:57  0.083 sec   1.0                0.3738466452376305
0.2766159701287137   0.13976131415543075
     2024-02-12 01:31:57  0.097 sec   2.0                0.3758367230594093
0.2771066727540383   0.14125324240003512
     2024-02-12 01:31:57  0.112 sec   3.0                0.3738767737866765
0.27557006541104856  0.13978384197713367
     2024-02-12 01:31:57  0.125 sec   4.0                0.3745703666395875
0.27647324328029943  0.140302959564515
     2024-02-12 01:31:57  0.139 sec   5.0                0.37629672620846083
0.2774631770522253   0.14159922615520534
     2024-02-12 01:31:57  0.152 sec   6.0                0.3752783792530109
0.2767983291039734   0.14083386193476666
     2024-02-12 01:31:57  0.163 sec   7.0                0.37484293332560986
0.2769982555564671   0.14050722466414758
     2024-02-12 01:31:57  0.177 sec   8.0                0.37521236000333935
0.27808066706661977  0.14078431509927553
     2024-02-12 01:31:57  0.190 sec   9.0                0.37477845128768894
0.2779314124674052   0.14045888754959862
---  ---                  ---         ---                ---
---                  ---
     2024-02-12 01:31:57  0.476 sec   41.0               0.3711076247558793
```

```
0.2786895663566569   0.1377208691519505
     2024-02-12 01:31:57  0.484 sec   42.0               0.37119114742074927
0.2787229389099004   0.13778286792353242
     2024-02-12 01:31:57  0.492 sec   43.0               0.3713079977330354
0.27892082298783216  0.13786962918051585
     2024-02-12 01:31:57  0.499 sec   44.0               0.3712919054350987
0.2789643131947148   0.13785767904162627
     2024-02-12 01:31:57  0.506 sec   45.0               0.3712537644862379
0.27896472457303206  0.13782935764520302
     2024-02-12 01:31:57  0.514 sec   46.0               0.37128502102701155
0.27892863578494576  0.1378525668390284
     2024-02-12 01:31:57  0.521 sec   47.0               0.37132178195460913
0.27895574903889897  0.13787986575394628
     2024-02-12 01:31:57  0.528 sec   48.0               0.37131847148137587
0.27899213266293826  0.13787740726326536
     2024-02-12 01:31:57  0.536 sec   49.0               0.3713034282264283
0.27895589944842775  0.1378662358126984
     2024-02-12 01:31:57  0.545 sec   50.0               0.3712342735821513
0.2788963132837725   0.13781488588206756
[51 rows x 7 columns]


Variable Importances:
variable                             relative_importance    scaled_importance
percentage
------------------------------------  ---------------------  -------------------
------------
Month-to-month                       3728.98                1
0.28983
MonthlyCharges_to_TotalCharges_Ratio  2302.27                0.617399
0.178941
Electronic check                     1454.53                0.39006
0.113051
tenure                               1426.67                0.38259
0.110886
MonthlyCharges_log                   1119.37                0.300181
0.0870016
TotalCharges_Tenure_Ratio            1072.73                0.287674
0.0833767
TotalCharges                         905.671                0.242874
0.0703922
MonthlyCharges                       732.634                0.196471
0.0569431
One year                             71.7401                0.0192385
0.00557592
Mailed check                         35.9773                0.00964805
0.0027963
```

```
Credit card (automatic)                 8.80259               0.00236059
0.000684171
Bank transfer (automatic)               6.70469               0.001798
0.000521114

[tips]
Use `model.explain()` to inspect the model.
--
Use `h2o.display.toggle_user_tips()` to switch on/off this section.
```

The features contributing the most to the model's decision-making process, based on the variable importances, are listed in the `Variable Importances` section. The top features along with their relative importance:

```
Month-to-month: 289.83%
MonthlyCharges_to_TotalCharges_Ratio: 178.94%
Electronic check: 113.05%
tenure: 110.89%
MonthlyCharges_log: 87.00%
TotalCharges_Tenure_Ratio: 83.38%
TotalCharges: 70.39%
MonthlyCharges: 56.94%
One year: 5.58%
Mailed check: 2.80%
Credit card (automatic): 0.68%
Bank transfer (automatic): 0.52%
```

These percentages represent the relative importance of each feature in the model. Features with higher percentages are considered more important in influencing the model's predictions. These are, `Month-to-month, MonthlyCharges_to_TotalCharges_Ratio, and Electronic check`

0.14 Evaluate DT model performance

[28]:
```python
def evaluate_model(model, X, y_true):
    y_pred = model.predict(X)
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)
    print(f"Accuracy: {accuracy:.4f}, Precision: {precision:.4f}, Recall: {recall:.4f}, F1 Score: {f1:.4f}")

print("Evaluation of Decision Tree Model:")
evaluate_model(dt_model_tuned, X_test, y_test)
```

```
Evaluation of Decision Tree Model:
Accuracy: 0.7871, Precision: 0.6763, Recall: 0.3753, F1 Score: 0.4828
```

Accuracy (0.7871) - The model achieves an accuracy of approximately 78.71%, indicating that 78.71% of the predictions are correct.

Precision (0.6763) - A precision of 0.6763 suggests that around 67.63% of the instances predicted as positive by the model are indeed positive.

Recall (0.3753) - It measures the model's ability to capture all the positive instances. A recall of 0.3753 means that the model is able to recall or identify approximately 37.53% of the actual positive instances.

F1 Score (0.4828) - An F1 score of 0.4828 indicates a reasonable balance between precision and recall for the model.

0.15 Summary

In this analysis, we began by preprocessing the churn data, including the creation of dummy variables for categorical features and factorization of selected columns. We trained decision tree and H2o random forest model, initially evaluating the DT performance using accuracy, precision, recall, and F1 score metrics. The decision tree model was further refined through hyperparameter tuning using GridSearchCV to optimize the max_depth parameter.

The dataset is split into training and test sets. Subsequently, a Random Forest model is trained on the original data using H2O. Feature importances are visualized for the H2O Random Forest model. The H2O Random Forest undergoes hyperparameter tuning using a Cartesian search strategy. The best H2o Random Forest model is selected, and its performance is evaluated on the test set.