Week4_Assignment

February 12, 2024

[35]:
```
# ! pip install pandas h2o matplotlib seaborn scikit-learn
```

[36]:
```
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.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
```

0.1 Load and preprocess data for modelling

[37]:
```
df = pd.read_csv("new_churn_data.csv")

df
```

[37]:
```
      tenure  PhoneService        Contract              PaymentMethod  \
0          1           NaN  Month-to-month           Electronic check
1         34           NaN        One year               Mailed check
2          2           NaN  Month-to-month               Mailed check
3         45           NaN        One year  Bank transfer (automatic)
4          2           NaN  Month-to-month           Electronic check
…        …           …             …                        …
7027      24           NaN        One year               Mailed check
7028      72           NaN        One year    Credit card (automatic)
7029      11           NaN  Month-to-month           Electronic check
7030       4           NaN  Month-to-month               Mailed check
7031      66           NaN        Two year  Bank transfer (automatic)

      MonthlyCharges  TotalCharges  Churn  MonthlyCharges_log  \
0              29.85         29.85      0            3.396185
1              56.95       1889.50      0            4.042174
2              53.85        108.15      1            3.986202
3              42.30       1840.75      0            3.744787
```

```
4             70.70        151.65      1            4.258446
…              …            …     …                …
7027          84.80       1990.50      0            4.440296
7028         103.20       7362.90      0            4.636669
7029          29.60        346.45      0            3.387774
7030          74.40        306.60      1            4.309456
7031         105.65       6844.50      0            4.660132

      TotalCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
0                     29.850000                              1.000000
1                     55.573529                              0.030140
2                     54.075000                              0.497920
3                     40.905556                              0.022980
4                     75.825000                              0.466205
…                       …                                     …
7027                  82.937500                              0.042602
7028                 102.262500                              0.014016
7029                  31.495455                              0.085438
7030                  76.650000                              0.242661
7031                 103.704545                              0.015436

      customerID
0              1
1              2
2              3
3              4
4              5
…            …
7027        7028
7028        7029
7029        7030
7030        7031
7031        7032

[7032 rows x 11 columns]
```

[38]:

```
df.drop(columns=['PhoneService', 'customerID'], inplace=True)
df.head()
```

[38]:

```
   tenure        Contract              PaymentMethod  MonthlyCharges  \
0       1  Month-to-month           Electronic check           29.85
1      34        One year               Mailed check           56.95
2       2  Month-to-month               Mailed check           53.85
3      45        One year  Bank transfer (automatic)           42.30
4       2  Month-to-month           Electronic check           70.70

   TotalCharges  Churn  MonthlyCharges_log  TotalCharges_Tenure_Ratio  \
```

```
0        29.85      0            3.396185                    29.850000
1      1889.50      0            4.042174                    55.573529
2       108.15      1            3.986202                    54.075000
3      1840.75      0            3.744787                    40.905556
4       151.65      1            4.258446                    75.825000

   MonthlyCharges_to_TotalCharges_Ratio
0                              1.000000
1                              0.030140
2                              0.497920
3                              0.022980
4                              0.466205
```

[39]:
```
payment_method_dummies = pd.get_dummies(df['PaymentMethod'])
contract_dummies = pd.get_dummies(df['Contract'])

df = pd.concat([df, payment_method_dummies, contract_dummies], axis=1)
df.head()
```

[39]:
```
   tenure        Contract              PaymentMethod  MonthlyCharges  \
0       1  Month-to-month           Electronic check           29.85
1      34        One year               Mailed check           56.95
2       2  Month-to-month               Mailed check           53.85
3      45        One year  Bank transfer (automatic)           42.30
4       2  Month-to-month           Electronic check           70.70

   TotalCharges  Churn  MonthlyCharges_log  TotalCharges_Tenure_Ratio  \
0        29.85      0            3.396185                  29.850000
1      1889.50      0            4.042174                  55.573529
2       108.15      1            3.986202                  54.075000
3      1840.75      0            3.744787                  40.905556
4       151.65      1            4.258446                  75.825000

   MonthlyCharges_to_TotalCharges_Ratio  Bank transfer (automatic)  \
0                              1.000000                      False
1                              0.030140                      False
2                              0.497920                      False
3                              0.022980                       True
4                              0.466205                      False

   Credit card (automatic)  Electronic check  Mailed check  Month-to-month  \
0                    False              True         False            True
1                    False             False          True           False
2                    False             False          True            True
3                    False             False         False           False
4                    False              True         False            True
```

```
   One year  Two year
0     False     False
1      True     False
2     False     False
3      True     False
4     False     False
```

[40]:
```python
df.drop(columns=['PaymentMethod', 'Contract'], inplace=True)
df
```

[40]:
```
      tenure  MonthlyCharges  TotalCharges  Churn  MonthlyCharges_log  \
0          1           29.85         29.85      0            3.396185
1         34           56.95       1889.50      0            4.042174
2          2           53.85        108.15      1            3.986202
3         45           42.30       1840.75      0            3.744787
4          2           70.70        151.65      1            4.258446
…        …             …             …   …                 …
7027      24           84.80       1990.50      0            4.440296
7028      72          103.20       7362.90      0            4.636669
7029      11           29.60        346.45      0            3.387774
7030       4           74.40        306.60      1            4.309456
7031      66          105.65       6844.50      0            4.660132

      TotalCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
0                     29.850000                              1.000000
1                     55.573529                              0.030140
2                     54.075000                              0.497920
3                     40.905556                              0.022980
4                     75.825000                              0.466205
…                           …                                   …
7027                  82.937500                              0.042602
7028                 102.262500                              0.014016
7029                  31.495455                              0.085438
7030                  76.650000                              0.242661
7031                 103.704545                              0.015436

      Bank transfer (automatic)  Credit card (automatic)  Electronic check  \
0                         False                    False              True
1                         False                    False             False
2                         False                    False             False
3                          True                    False             False
4                         False                    False              True
…                           …                       …               …
7027                      False                    False             False
7028                      False                     True             False
7029                      False                    False              True
7030                      False                    False             False
```

```
7031                          True                     False                 False

      Mailed check  Month-to-month  One year  Two year
0            False            True     False     False
1             True           False      True     False
2             True            True     False     False
3            False           False      True     False
4            False            True     False     False
…             …             …        …        …
7027          True           False      True     False
7028         False           False      True     False
7029         False            True     False     False
7030          True            True     False     False
7031         False           False     False      True

[7032 rows x 14 columns]
```

[41]:
```python
dummy_columns = ['Electronic check', 'Mailed check', 'Bank transfer (automatic)', 'Credit card (automatic)', 'Month-to-month', 'One year', 'Two year']

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

df.sample(5)
```

[41]:
```
      tenure  MonthlyCharges  TotalCharges  Churn  MonthlyCharges_log  \
4507      15           83.20       1130.00      0            4.421247
4722      31           96.60       2877.95      0            4.570579
3243      10           86.65        856.65      1            4.461877
3306      48           44.80       2104.55      0            3.802208
2423      38           99.25       3777.15      1            4.597642

      TotalCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
4507                  75.333333                              0.073628
4722                  92.837097                              0.033566
3243                  85.665000                              0.101150
3306                  43.844792                              0.021287
2423                  99.398684                              0.026276

      Bank transfer (automatic)  Credit card (automatic)  Electronic check  \
4507                          1                        0                 1
4722                          1                        0                 1
3243                          0                        0                 0
3306                          0                        0                 0
2423                          1                        0                 1
```

```
      Mailed check  Month-to-month  One year  Two year
4507             0               0         0         0
4722             0               0         0         0
3243             0               0         0         0
3306             0               0         0         0
2423             0               0         0         0
```

[42]:
```
df.isna().sum()
```

[42]:
```
tenure                                   0
MonthlyCharges                           0
TotalCharges                             0
Churn                                    0
MonthlyCharges_log                       0
TotalCharges_Tenure_Ratio                0
MonthlyCharges_to_TotalCharges_Ratio     0
Bank transfer (automatic)                0
Credit card (automatic)                  0
Electronic check                         0
Mailed check                             0
Month-to-month                           0
One year                                 0
Two year                                 0
dtype: int64
```

0.2 Split data into feature and targets

[43]:
```
X = df.drop('Churn', axis=1)
y = df['Churn']
```

0.3 Training and Test sets

[44]:
```
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 decision tree

[45]:
```
dt_model = DecisionTreeClassifier(max_depth=3)
dt_model.fit(X_train, y_train)
```

[45]:
```
DecisionTreeClassifier(max_depth=3)
```

[46]:
```
tr= export_text(dt_model, feature_names=list(X.columns))
print(tr)
```

```
|--- Month-to-month <= 0.50
|   |--- MonthlyCharges_log <= 4.21
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.32
```

```
|   |   |   |--- class: 0
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.32
|   |   |   |--- class: 0
|   |--- MonthlyCharges_log >  4.21
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.08
|   |   |   |--- class: 0
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.08
|   |   |   |--- class: 1
|--- Month-to-month >  0.50
|   |--- MonthlyCharges_log <= 4.54
|   |   |--- One year <= 0.50
|   |   |   |--- class: 0
|   |   |--- One year >  0.50
|   |   |   |--- class: 0
|   |--- MonthlyCharges_log >  4.54
|   |   |--- TotalCharges <= 6586.10
|   |   |   |--- class: 0
|   |   |--- TotalCharges >  6586.10
|   |   |   |--- class: 0
```

The tree's structure indicates that customers with shorter month-to-month contract durations, lower monthly charges, and a specific ratio of monthly charges to total charges are more likely to stay with the service (class: 0 - no churn). On the other hand, customers with month-to-month contracts, higher monthly charges, and a different ratio are more prone to churn (class: 1). The tree also suggests that customers with longer-term contracts and certain ranges of total charges are less likely to churn. This initial decision tree provides a snapshot of potential predictors for churn.

0.5 Tune hyperparameters for Decision tree

[47]:
```python
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)
```

[47]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'max_depth': [3, 5, 7, 10]})
```

[48]:
```python
best_max_depth = grid_search.best_params_['max_depth']
best_max_depth
```

[48]:
```
5
```

0.6 Fit and plot the DT with best hyperparameters

[49]:
```python
dt_model_tuned = DecisionTreeClassifier(max_depth=best_max_depth)
dt_model_tuned.fit(X_train, y_train)
```

[49]: DecisionTreeClassifier(max_depth=5)

[50]:
```python
tree_rules_tuned = export_text(dt_model_tuned, feature_names=list(X.columns))
print(tree_rules_tuned)
```

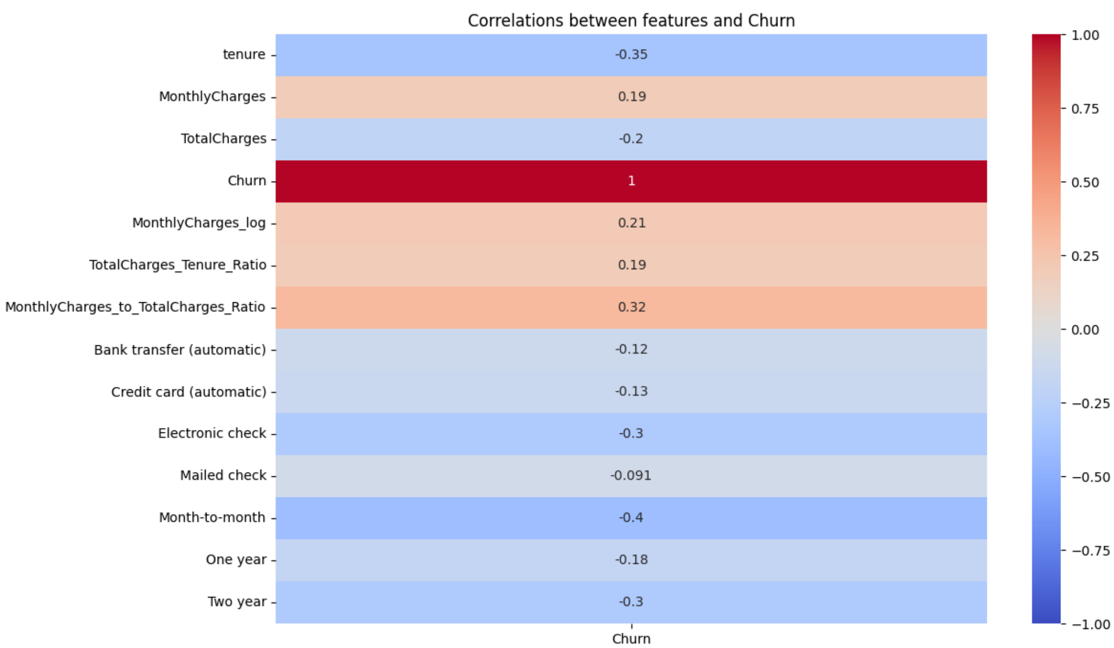
```
|--- Month-to-month <= 0.50
|   |--- MonthlyCharges <= 67.60
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.32
|   |   |   |--- MonthlyCharges <= 27.45
|   |   |   |   |--- TotalCharges_Tenure_Ratio <= 16.39
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- TotalCharges_Tenure_Ratio >  16.39
|   |   |   |   |   |--- class: 0
|   |   |   |--- MonthlyCharges >  27.45
|   |   |   |   |--- TotalCharges <= 310.90
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges >  310.90
|   |   |   |   |   |--- class: 0
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.32
|   |   |   |--- MonthlyCharges_log <= 3.04
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.61
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.61
|   |   |   |   |   |--- class: 0
|   |   |   |--- MonthlyCharges_log >  3.04
|   |   |   |   |--- Mailed check <= 0.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- Mailed check >  0.50
|   |   |   |   |   |--- class: 0
|   |--- MonthlyCharges >  67.60
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.08
|   |   |   |--- Electronic check <= 0.50
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.02
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.02
|   |   |   |   |   |--- class: 1
|   |   |   |--- Electronic check >  0.50
|   |   |   |   |--- TotalCharges_Tenure_Ratio <= 100.06
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges_Tenure_Ratio >  100.06
|   |   |   |   |   |--- class: 0
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.08
|   |   |   |--- TotalCharges <= 120.00
|   |   |   |   |--- TotalCharges_Tenure_Ratio <= 69.88
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- TotalCharges_Tenure_Ratio >  69.88
|   |   |   |   |   |--- class: 1
|   |   |   |--- TotalCharges >  120.00
```

```
|   |   |   |   |--- TotalCharges_Tenure_Ratio <= 81.18
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- TotalCharges_Tenure_Ratio >  81.18
|   |   |   |   |   |--- class: 1
|--- Month-to-month >  0.50
|   |--- MonthlyCharges_log <= 4.54
|   |   |--- One year <= 0.50
|   |   |   |--- Electronic check <= 0.50
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.02
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.02
|   |   |   |   |   |--- class: 0
|   |   |   |--- Electronic check >  0.50
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.02
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.02
|   |   |   |   |   |--- class: 0
|   |   |--- One year >  0.50
|   |   |   |--- TotalCharges_Tenure_Ratio <= 27.01
|   |   |   |   |--- TotalCharges_Tenure_Ratio <= 14.42
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges_Tenure_Ratio >  14.42
|   |   |   |   |   |--- class: 0
|   |   |   |--- TotalCharges_Tenure_Ratio >  27.01
|   |   |   |   |--- TotalCharges_Tenure_Ratio <= 27.11
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- TotalCharges_Tenure_Ratio >  27.11
|   |   |   |   |   |--- class: 0
|   |--- MonthlyCharges_log >  4.54
|   |   |--- TotalCharges <= 6586.10
|   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.01
|   |   |   |   |--- class: 1
|   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.01
|   |   |   |   |--- MonthlyCharges <= 103.22
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges >  103.22
|   |   |   |   |   |--- class: 0
|   |   |--- TotalCharges >  6586.10
|   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.01
|   |   |   |   |--- TotalCharges <= 8678.62
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges >  8678.62
|   |   |   |   |   |--- class: 1
|   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.01
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.01
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.01
|   |   |   |   |   |--- class: 0
```

After hyperparameter tuning, the decision tree with the best_max_depth of 5 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. This suggests that a deeper decision tree with increased complexity may capture subtle patterns that contribute to the prediction of churn, potentially improving the model's performance.

0.7 Plot correlations btn features and targets

[51]:
```
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()
```



0.8 Start and connect to the H2o cluster

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

[53]:
```
hf = h2o.H2OFrame(df)
```

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

0.9 Training and test sets

[54]:
```
train, test = hf.split_frame(ratios=[0.8], seed=42)
```

0.10 Fit H20 RF

[55]:
```
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%
```

[55]:
```
Model Details
=============
H2ORandomForestEstimator : Distributed Random Forest
Model Key: DRF_model_python_1707690266499_2


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                          537964                 20
20           20           784           920           851.3

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

MSE: 0.16084093394425325
RMSE: 0.40104978985688705
MAE: 0.27389182194743317
RMSLE: 0.2819312492153419
Mean Residual Deviance: 0.16084093394425325

Scoring History:
     timestamp            duration    number_of_trees    training_rmse
training_mae         training_deviance
---  -------------------  ----------  -----------------  -------------------
-------------------  -------------------
```

```
     2024-02-12 01:30:35  0.025 sec   0.0                 nan
nan                  nan
     2024-02-12 01:30:36  0.111 sec   1.0                 0.5198158101265961
0.27603101380822076  0.27020847645756935
     2024-02-12 01:30:36  0.166 sec   2.0                 0.5063120246924118
0.27769924642049054  0.2563518663481294
     2024-02-12 01:30:36  0.209 sec   3.0                 0.4952374859378511
0.2764261701424577   0.24526016747804327
     2024-02-12 01:30:36  0.260 sec   4.0                 0.47787931034835746
0.27023942918988414  0.22836863525902173
     2024-02-12 01:30:36  0.295 sec   5.0                 0.47395754484278324
0.27661229272439203  0.22463575431339888
     2024-02-12 01:30:36  0.330 sec   6.0                 0.46490207625165736
0.276509020226267    0.21613394050310183
     2024-02-12 01:30:36  0.364 sec   7.0                 0.45801188443179486
0.27622033401866963  0.20977488628076382
     2024-02-12 01:30:36  0.392 sec   8.0                 0.44962727891965776
0.2744712195777388   0.2021646899486957
     2024-02-12 01:30:36  0.420 sec   9.0                 0.4413389816863617
0.27246185799049255  0.19478009675595473
---  ---                  ---         ---                 ---
---                  ---
     2024-02-12 01:30:37  2.005 sec   41.0                0.40274415145040515
0.273654359286112    0.16220285152750688
     2024-02-12 01:30:38  2.083 sec   42.0                0.40295684413333355
0.27400986199994226  0.16237421823389567
     2024-02-12 01:30:38  2.135 sec   43.0                0.4026217973389886
0.2738468013296778   0.1621043116924776
     2024-02-12 01:30:38  2.195 sec   44.0                0.402564445160092
0.27397787910422994  0.1620581325070527
     2024-02-12 01:30:38  2.244 sec   45.0                0.4022429468734082
0.27370611723455945  0.1617993883094035
     2024-02-12 01:30:38  2.287 sec   46.0                0.4021593480083743
0.2739029694532263   0.1617321411905207
     2024-02-12 01:30:38  2.334 sec   47.0                0.4019764552243372
0.27396939454576225  0.1615850705547236
     2024-02-12 01:30:38  2.373 sec   48.0                0.4018265388914359
0.2740408747538355   0.16146456735747064
     2024-02-12 01:30:38  2.417 sec   49.0                0.4012650058347152
0.2739264124781572   0.161013604907534
     2024-02-12 01:30:38  2.458 sec   50.0                0.40104978985688705
0.27389182194743317  0.16084093394425325
[51 rows x 7 columns]


Variable Importances:
variable                              relative_importance    scaled_importance
```

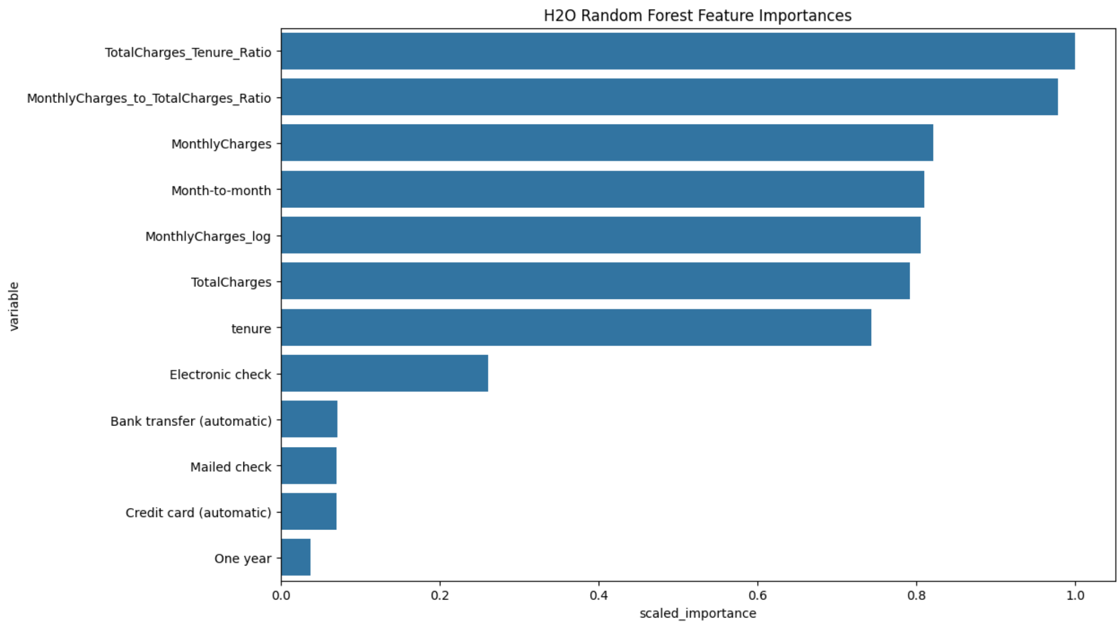
```
percentage
------------------------------------  ---------------------  -------------------
------------
TotalCharges_Tenure_Ratio             5527.38                1
0.154756
MonthlyCharges_to_TotalCharges_Ratio  5409.61                0.978694
0.151459
MonthlyCharges                        4537.4                 0.820896
0.127039
Month-to-month                        4473.87                0.809402
0.12526
MonthlyCharges_log                    4453.21                0.805665
0.124682
TotalCharges                          4375.09                0.79153
0.122494
tenure                                4105.62                0.74278
0.11495
Electronic check                      1445.49                0.261514
0.0404709
Bank transfer (automatic)             398.011                0.0720073
0.0111436
Mailed check                          390.518                0.0706516
0.0109338
Credit card (automatic)               390.039                0.0705649
0.0109204
One year                              210.383                0.038062
0.00589034

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

The H2ORandomForestEstimator was employed, and the model's key and summary statistics, such as the number of trees, model size, and depth metrics, are presented. The model's performance metrics on the training data include mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and mean residual deviance, providing insights into the model's accuracy and predictive capabilities.

The scoring history reveals the training progress over different iterations, showing the improvement in metrics as the number of trees increases. Furthermore, the variable importances indicate the significance of each feature in predicting churn, with variables like TotalCharges_Tenure_Ratio and MonthlyCharges_to_TotalCharges_Ratio contributing the most to the model's predictive power. This information is crucial for understanding the model's performance, identifying influential features, and assessing its generalization ability on unseen data.

0.11 Plot H2o RF feature importances

[56]:
```
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 Fit sklearn RF to data

[57]:
```
X = df.drop('Churn', axis=1)
y = df['Churn']
rf_sklearn = RandomForestClassifier(n_estimators=100, random_state=42)
rf_sklearn.fit(X, y)
```

[57]:
```
RandomForestClassifier(random_state=42)
```

0.13 sklearn Feature selection

[58]:
```
sfm = SelectFromModel(rf_sklearn, threshold=0.1)
sfm.fit(X, y)
selected_features = X.columns[sfm.get_support()]
```

0.14 Display features

[59]:
```
print("Selected features using sklearn Random Forest:", selected_features)
```

```
Selected features using sklearn Random Forest: Index(['tenure',
'MonthlyCharges', 'TotalCharges', 'MonthlyCharges_log',
       'TotalCharges_Tenure_Ratio', 'MonthlyCharges_to_TotalCharges_Ratio'],
      dtype='object')
```

0.15 Hyperparameter tuning for sklearn RF

[60]:
```
param_grid = {'n_estimators': [50, 100, 200], 'max_depth': [None, 5, 10, 20]}

grid_search = GridSearchCV(rf_sklearn, param_grid, cv=5)
grid_search.fit(X, y)
```

[60]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=42),
             param_grid={'max_depth': [None, 5, 10, 20],
                         'n_estimators': [50, 100, 200]})
```

0.16 Best hyperparameters

[67]:
```
best_params_sklearn = grid_search.best_params_
best_params_sklearn
```

[67]:
```
{'max_depth': 5, 'n_estimators': 200}
```

0.17 Fit sklearn Random Forest with best hyperparameters

[62]:
```
rf_sklearn_tuned = RandomForestClassifier(**best_params_sklearn)
rf_sklearn_tuned.fit(X, y)
```

[62]:
```
RandomForestClassifier(max_depth=5, n_estimators=200)
```

0.18 Evaluate sklearn Random Forest model

[63]:
```
y_pred_sklearn = rf_sklearn_tuned.predict(X)
accuracy_sklearn = accuracy_score(y, y_pred_sklearn)
precision_sklearn = precision_score(y, y_pred_sklearn)
recall_sklearn = recall_score(y, y_pred_sklearn)
f1_sklearn = f1_score(y, y_pred_sklearn)

print("Evaluation of sklearn Random Forest Model:")
print(f"Accuracy: {accuracy_sklearn:.4f}, Precision: {precision_sklearn:.4f}, 
 ↪Recall: {recall_sklearn:.4f}, F1 Score: {f1_sklearn:.4f}")
```

```
Evaluation of sklearn Random Forest Model:
Accuracy: 0.8025, Precision: 0.6875, Recall: 0.4708, F1 Score: 0.5589
```

Accuracy (0.8025) - It represents the overall correctness of the model, calculated as the ratio of correctly predicted instances to the total number of instances. The model correctly predicted approximately 80.25% of the instances.

Precision (0.6875) - A measure of how many of the instances predicted as positive are actually positive. It is calculated as the ratio of true positive predictions to the total number of positive predictions. A precision of 0.6875 means that when the model predicts a positive outcome, it is correct about 68.75% of the time.

Recall (0.4708) - Recall/sensitivity or true positive rate, measures the proportion of actual positive instances that the model correctly identifies. A recall of 0.4708 indicates that the model captures approximately 47.08% of all positive instances.

F1 Score (0.5589) - The F1 score is the harmonic mean of precision and recall, providing a balance between the two metrics. It is useful when there is an uneven class distribution. An F1 score of 0.5589 reflects a trade-off between precision and recall, combining both aspects of the model's performance.

0.19 Hyperparameter tuning for H2O Random Forest

[68]:
```
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%
```

[68]:
```
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
     10           200.0     rf_grid_model_8   0.1401909249657123
     10           100.0     rf_grid_model_5   0.14089808435792933
     10           200.0     rf_grid_model_17  0.14179692707213173
     3            200.0     rf_grid_model_27  0.14187975641595388
---  ---          ---       ---               ---
     3            100.0     rf_grid_model_23  0.14255671796128458
     10           100.0     rf_grid_model_14  0.1429436019240686
```

```
    10          50.0      rf_grid_model_11  0.14360881368685938
    10          50.0      rf_grid_model_2   0.14362929618835682
    20          200.0     rf_grid_model_9   0.148251141151126
    20          100.0     rf_grid_model_6   0.15147812594614404
    20          50.0      rf_grid_model_3   0.15418989928987115
    20          200.0     rf_grid_model_18  0.1556643356409992
    20          100.0     rf_grid_model_15  0.15720762584792694
    20          50.0      rf_grid_model_12  0.15849556898288003
[21 rows x 5 columns]
```

max_depth - This hyperparameter represents the maximum depth of the individual trees in the ensemble. We've experimented with different values for 'max_depth' (3, 5, 10, 20).

ntrees - The number of trees in the random forest i.e.,trees (50, 100, 200).

model_ids - These are the identifiers for each model generated during the grid search.

residual_deviance - The residual deviance is a measure of how well the model fits the data. It's a measure of the difference between the predicted values and the actual values. Lower values indicate a better fit.

e.g., the best-performing model in terms of residual deviance has 'max_depth' of 5 and 'ntrees' of 50, with a residual deviance of 0.1378149. The grid search allows for comparison of the performance of models with different hyperparameter values and identify the combination that yields the best results.

0.20 Best H2o RF model

[69]:
```
best_rf_h2o = grid.models[0]
best_rf_h2o
```

[69]:
```
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`

0.21 Summary

Analysis of a churn prediction dataset is performed using both H2O and scikit-learn machine learning frameworks. The initial steps include reading the data, preprocessing by dropping unnecessary columns, creating dummy variables for categorical features, and converting the Pandas DataFrame to an H2O DataFrame. The dataset is split into training and test sets. Subsequently, a Random Forest model is trained on the original data using both H2O and scikit-learn. Feature importances are visualized for the H2O Random Forest model. Scikit-learn's Random Forest is employed for feature selection and hyperparameter tuning through GridSearchCV. The best hyperparameters are then used to train the tuned scikit-learn 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.