Phase 2 - Machine Learning with H2O.ai

Build - 4 new ML models using H2O.ai framework

- GLM - Generalized Linear Model
- Random Forest
- GBM
- XGBoost

Recap

Info about model evaluation - accuracy metric vs recall

- The global metric accuracy will be used to evaluate the models between all frameworks (xgb, lgbm, sklearn, h2o.ai and Apache Spark)

The last notebook build ml models using python will provide some additional techniques, such as:

- Unbalanced classification and class weight
- Smote technique for oversampling the training dataset
- Standard Scale vs. default data and
- Finally, exchange the global metric accuracy and use recall metric < recall or Sensitivity or True positive rate (TPR) >
  Recall metric is a better metric than accuracy to evaluate this type of scenario (customer churn)

Additional info: http://docs.h2o.ai/h2o/latest-stable/h2o-docs/performance-and-prediction.html (http://docs.h2o.ai/h2o/latest-stable/h2o-docs/performance-and-prediction.html)

Starting process...

In [2]:

```
import pandas as pd
import seaborn as sns

from sklearn.model_selection import train_test_split

## Metrics - Classification
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score

## H2O
import h2o

## ML Models
from h2o.estimators import (H2OGeneralizedLinearEstimator, H2OGradientBoostingEstimator
,
                            H2ORandomForestEstimator, H2OXGBoostEstimator)
```

H2O - connection to h2o cluster

In [3]:

```
## connect to h2o cluster and remove all object
h2o.connect(ip='192.168.56.102')
h2o.remove_all()
```

```
Connecting to H2O server at http://192.168.56.102:54321 ... successful.
```

H2O cluster uptime:	1 hour 22 mins
H2O cluster timezone:	America/Sao_Paulo
H2O data parsing timezone:	UTC
H2O cluster version:	3.26.0.3
H2O cluster version age:	7 months and 22 days !!!
H2O cluster name:	userds1
H2O cluster total nodes:	1
H2O cluster free memory:	5.746 Gb
H2O cluster total cores:	1
H2O cluster allowed cores:	1
H2O cluster status:	locked, healthy
H2O connection url:	http://192.168.56.102:54321
H2O connection proxy:	None
H2O internal security:	False
H2O API Extensions:	Amazon S3, XGBoost, Algos, AutoML, Core V3, Core V4
Python version:	3.7.3 final

Load and prepare the dataset to build ML models

In [4]:

```
## Load dataset
df = pd.read_csv('../data/WA_Fn-UseC_-Telco-Customer-Churn.csv')

## Filter columns and set values
df.loc[(df.tenure==0) & (df.TotalCharges == ' '), ['TotalCharges', 'tenure']] = 0
df['TotalCharges'] = df['TotalCharges'].astype('float')

target = 'Churn'
current_features = ['tenure', 'MonthlyCharges', 'TotalCharges', 'gender', 'PaymentMetho
d' , 'Churn', 'Contract']

df = df[current_features]
df.head(3)
```

Out[4]:

	tenure	MonthlyCharges	TotalCharges	gender	PaymentMethod	Churn	Contract
0	1	29.85	29.85	Female	Electronic check	No	Month-to-month
1	34	56.95	1889.50	Male	Mailed check	No	One year
2	2	53.85	108.15	Male	Mailed check	Yes	Month-to-month

Load dataset into H2O cluster

In [5]:

```
target = 'Churn'
features = df.columns.to_list()
features.remove(target)

X = df[features]
y = df[target]

SEED = 42
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=
SEED)

## Label Encode - will be used later to evaluate model performance
target_1_0 = lambda x: ['No', 'Yes'].index(x)
y_true_test = y_test.apply(target_1_0).values

train_X = X_train.copy()
train_X[target] = y_train

test_X = X_test.copy()
test_X[target] = y_test

## Convert to h2o Frame
train_h2o = h2o.H2OFrame(train_X, destination_frame='train.hex')
test_h2o = h2o.H2OFrame(test_X, destination_frame='test.hex')
```

```
Parse progress: |██████████████████████████████████████████████████████████
| 100%
Parse progress: |██████████████████████████████████████████████████████████
| 100%
```

H2O - Build Machine Learning Models

H2O - RANDOM FOREST

- Accuracy: 71,78%

In [6]:

```
## Random Forest
model_rf = H2ORandomForestEstimator(seed = SEED)
model_rf.train(
    x = features,
    y = target,
    training_frame = train_h2o,
    model_id = 'fit_rf.model'
)
ypred_RF_df = model_rf.predict(test_h2o).as_data_frame()
# model_rf.model_performance()

print('Random Forest')
y_pred_RF = ypred_RF_df['predict'].apply(target_1_0).values

# print_confusion_matrix(y_true, y_pred)
print('Accuracy score: ', accuracy_score(y_true_test, y_pred_RF))
```

```
drf Model Build progress: |██████████████████████████████████████████████
| 100%
drf prediction progress: |███████████████████████████████████████████████
| 100%
Random Forest
Accuracy score:  0.7178494623655914
```

H2O GBM

- Accuracy: 77,07%

In [7]:

```
model_gbm = H2OGradientBoostingEstimator(seed = SEED)
model_gbm.train(
    x = features,
    y = target,
    training_frame = train_h2o,
    model_id = 'fit_gbm.model'
)
# model_gbm.model_performance()

ypred_GBM_df = model_gbm.predict(test_h2o).as_data_frame()
y_pred = ypred_GBM_df['predict'].copy().apply(target_1_0).values


print('GBM')
# print_confusion_matrix(y_true, y_pred)
print('Accuracy score: ', accuracy_score(y_true_test, y_pred))
```

```
gbm Model Build progress: |██████████████████████████████████████████████
| 100%
gbm prediction progress: |███████████████████████████████████████████████
| 100%
GBM
Accuracy score:  0.770752688172043
```

H2O - GLM (generalized linear model)

- Accuracy: 76,64%

In [8]:

```
model_glm = H2OGeneralizedLinearEstimator(seed = SEED, family='binomial')
model_glm.train(
    x = features,
    y = target,
    training_frame = train_h2o,
    model_id = 'fit_glm.model'
)
# model_glm.model_performance()
ypred_GLM_df = model_glm.predict(test_h2o).as_data_frame()
y_pred = ypred_GLM_df['predict'].copy().apply(target_1_0).values

print('GLM')
# print_confusion_matrix(y_true, y_pred)
print('Accuracy score: ', accuracy_score(y_true_test, y_pred))
```

```
glm Model Build progress: |████████████████████████████████████████████████
| 100%
glm prediction progress: |█████████████████████████████████████████████████
| 100%
GLM
Accuracy score:  0.7664516129032258
```

H2O - XGB

- Accuracy: 79,18%

In [9]:

```
model_xgb = H2OXGBoostEstimator(seed = SEED)
model_xgb.train(
    x = features,
    y = target,
    training_frame = train_h2o,
    model_id = 'fit_xgb.model'
)
# model_xgb.model_performance()
ypred_XGB_df = model_xgb.predict(test_h2o).as_data_frame()
y_pred = ypred_XGB_df['predict'].copy().apply(target_1_0).values

print('XGB')
# print_confusion_matrix(y_true, y_pred)
print('Accuracy score: ', accuracy_score(y_true_test, y_pred))
```

```
xgboost Model Build progress: |████████████████████████████████████████████
| 100%
xgboost prediction progress: |█████████████████████████████████████████████
| 100%
XGB
Accuracy score:  0.7918279569892474
```

Export model

- H2O xgb have the highest accuracy score

In [10]:

```
## H2O export model
export_model_path = h2o.save_model(model=model_xgb, path="./ML_models/model_xgb_v1/", f
orce=True)
print('Export done!')
```

```
Export done!
```

Load the model and run prediction again to test the results

In [11]:

```
h2o_model_xgb = h2o.load_model(export_model_path)

# model_xgb.model_performance()
ypred_XGB_df = h2o_model_xgb.predict(test_h2o).as_data_frame()
y_pred = ypred_XGB_df['predict'].copy().apply(target_1_0).values

print('XGB')
# print_confusion_matrix(y_true, y_pred)
print('Accuracy score: ', accuracy_score(y_true_test, y_pred))
```

```
xgboost prediction progress: |████████████████████████████████████████████
| 100%
XGB
Accuracy score:  0.7918279569892474
```

Evaluation report

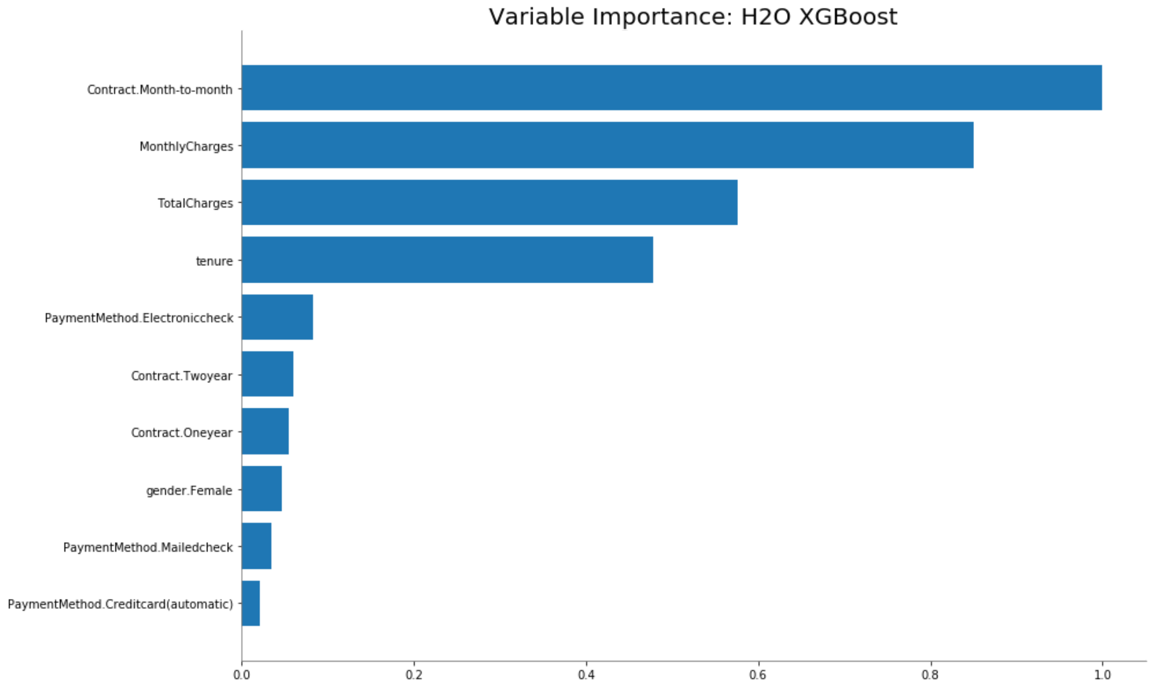
Confusion matrix - associated with XGB

- Accuracy: 79,18%

Plot Feature importance - H2O - xgb

In [13]:

```
model_xgb.varimp_plot()
```



Summary with h2o

- The xgb achieved the best accuracy and was exported to be used later

The most important features, characteristics that influence customer churn are:

- Contract_Month-to_Month
- MonthlyCharges
- TotalCharges and
- tenure

Let´s move on with ML model built using Apache Spark framework in the next notebook

In [14]:

```
!jupyter nbconvert --to html Phase_2_Build_ML_models_with_Python_3x6_h2o_ai.ipynb
```

In [ ]: