Ensemble Learning

Learning Objectives

By the end of this lesson, you will be able to:

- Define ensemble learning
- List different types of ensemble methods
- Build an intuition
- Apply different algorithms of ensemble learning using use cases

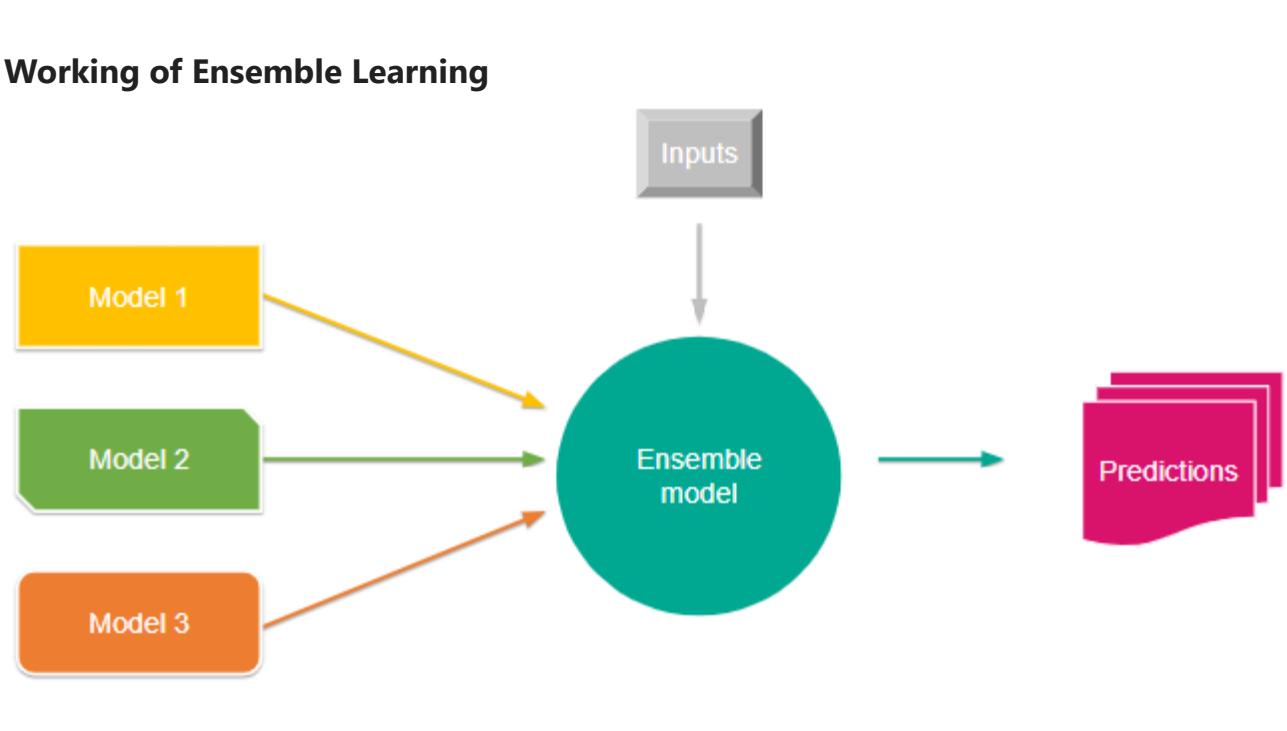
What Is Ensemble Learning?

Ensemble techniques combine individual models to improve the stability and predictive power of the model.

Ideology Behind Ensemble Learning:

- Certain models do well in modeling one aspect of the data, while others do well in modeling another.
- Instead of learning a single complex model, learn several simple models and combine their output to produce the final decision.
- Individual model variances and biases are balanced by the strength of other models in ensemble learning.
- Ensemble learning will provide a composite prediction where the final accuracy is better than the accuracy of individual models.

Working of Ensemble Learning



Significance of Ensemble Learning

- Robustness
  - Ensemble models incorporate the predictions from all the base learners
- Accuracy
  - Ensemble models deliver accurate predictions and have improved performances

Ensemble Learning Methods

- Techniques for creating an ensemble model
- Combine all weak learners to form an ensemble, or create an ensemble of well-chosen strong and diverse models

Steps Involved in Ensemble Methods

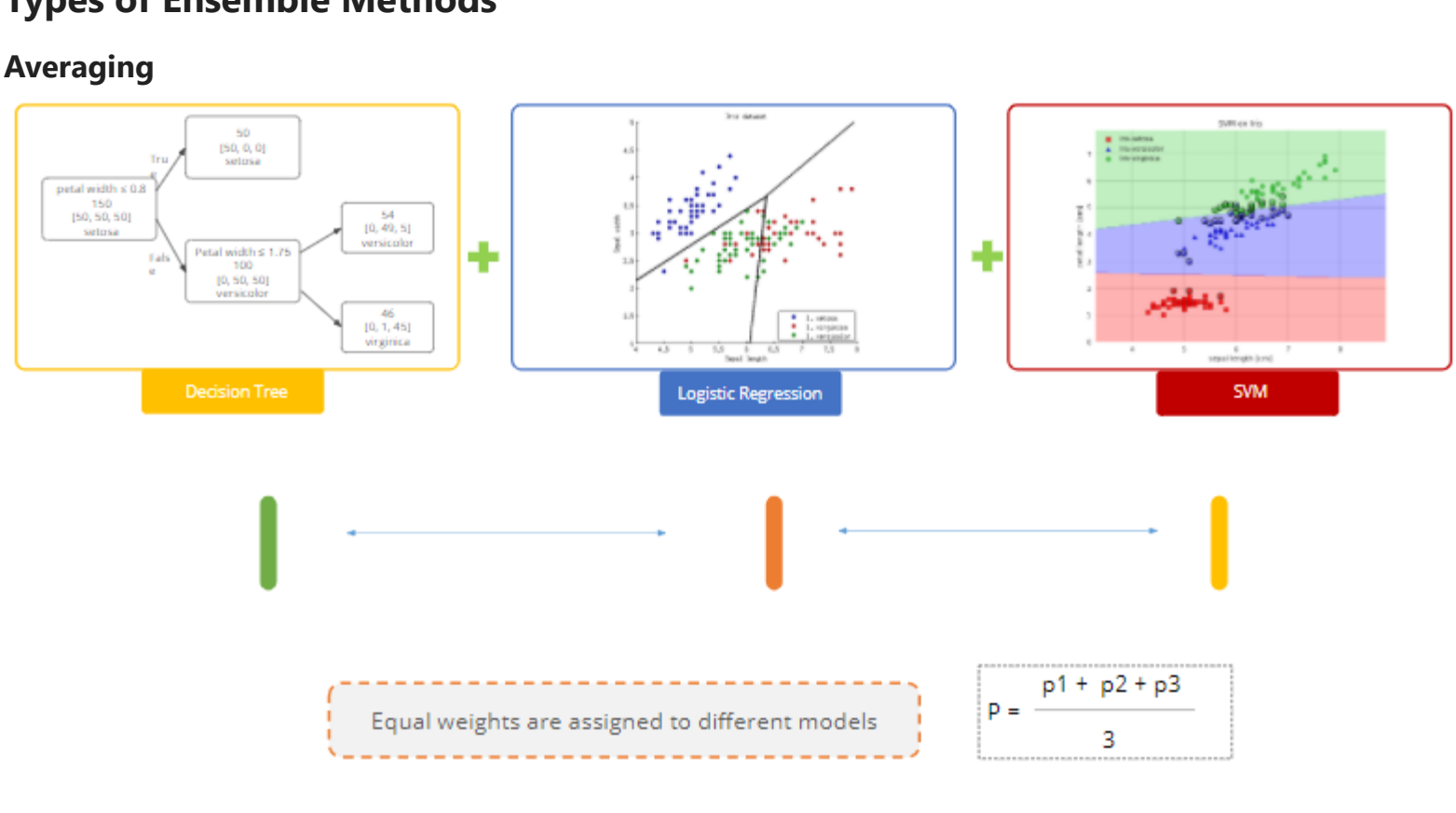
Every ensemble algorithm consists of two steps:

- Producing a cohort of predictions using simple ML algorithms
- Combining the predictions into one aggregated model

The ensemble can be achieved through several techniques.

Types of Ensemble Methods

Averaging



Weighted Averaging

Bagging Algorithms

Bootstrap Aggregation or bagging involves taking multiple samples from your training dataset (with replacement) and training a model for each sample.

The final output prediction is averaged across the predictions of all of the submodels.

The three bagging models covered in this section are as follows:

- Bagged Decision Trees
- Random Forest
- Extra Trees

1. Bagged Decision Trees

Bagging performs best with algorithms that have a high variance. A popular example is decision trees, often constructed without pruning.

Below, you can see an example of using the BaggingClassifier with the Classification and Regression Trees algorithm (DecisionTreeClassifier). A total of 100 trees are created.

- Scikit-learn is a Python library that provides a consistent interface for machine learning and statistical modeling, including classification, regression, clustering, and dimensionality reduction.
- Pandas is a Python library for data manipulation and analysis.

In [71]:
```
#Bagged Decision Trees for Classification
import pandas
from sklearn import model_selection
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier

url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = pandas.read_csv(url, names=names)
array = dataframe.values

X = array[:,0:8]
Y = array[:,8]

seed = 7

kfold = model_selection.KFold(n_splits=10, random_state=seed, shuffle=True)
cart = DecisionTreeClassifier()
num_trees = 100

model = BaggingClassifier(base_estimator=cart, n_estimators=num_trees, random_state=seed)

results = model_selection.cross_val_score(model, X, Y, cv=kfold)
print(results.mean())
```

```
0.7578263841421736
```

2. Random Forest

Random forest is an extension of bagged decision trees.

Samples of the training dataset are taken with replacement, but the trees are constructed in a way that reduces the correlation between individual classifiers. Specifically, rather than greedily choosing the best split point in the construction of the tree, only a random subset of features is considered for each split.

You can construct a Random Forest model for classification using the RandomForestClassifier class.

The example below provides a sample of Random Forest for classification with 100 trees and split points chosen from a random selection of three features.

In [72]:
```
#Random Forest Classification
import pandas
from sklearn import model_selection
from sklearn.ensemble import RandomForestClassifier

url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = pandas.read_csv(url, names=names)
array = dataframe.values

X = array[:,0:8]
Y = array[:,8]
seed = 7
num_trees = 100
max_features = 3

kfold = model_selection.KFold(n_splits=10, random_state=seed, shuffle=True)
model = RandomForestClassifier(n_estimators=num_trees, max_features=max_features)
results = model_selection.cross_val_score(model, X, Y, cv=kfold)
print(results.mean())
```

```
0.764354066985646
```

3. Extra Trees

Extra Trees are another modification of bagging where random trees are constructed from samples of the training dataset.

You can construct an Extra Trees model for classification using the ExtraTreesClassifier class.

The example below provides a demonstration of extra trees with a tree set of 100 and splits chosen from seven random features.

In [73]:
```
#Extra Trees Classification
import pandas
from sklearn import model_selection
from sklearn.ensemble import ExtraTreesClassifier
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = pandas.read_csv(url, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
seed = 7
num_trees = 100
max_features = 7
kfold = model_selection.KFold(n_splits=10, random_state=seed, shuffle=True)
model = ExtraTreesClassifier(n_estimators=num_trees, max_features=max_features)
results = model_selection.cross_val_score(model, X, Y, cv=kfold)
print(results.mean())
```

```
0.7577922077922079
```

Boosting Algorithms

Boosting ensemble algorithms create a sequence of models that attempts to correct the mistakes of the models before them in the sequence.

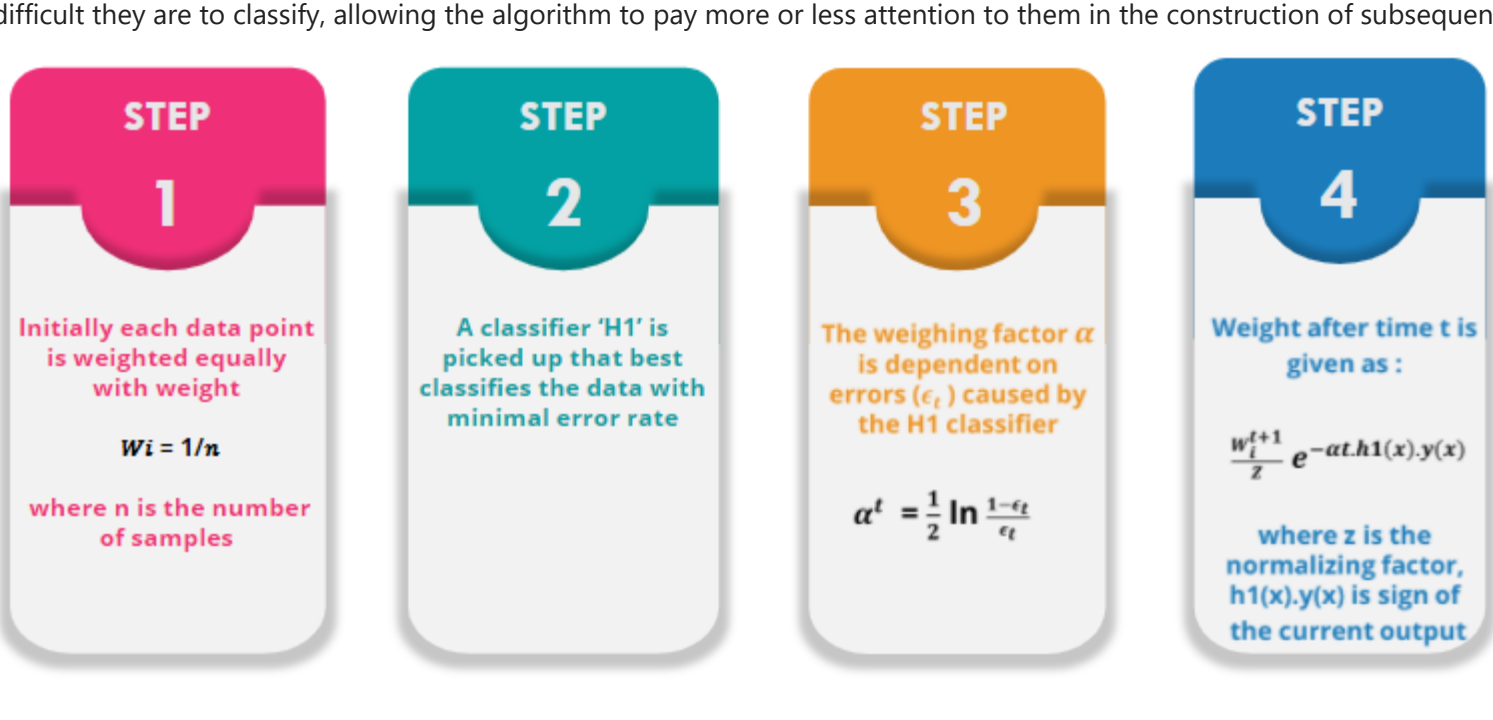
Once created, the models make predictions that may be weighted by their demonstrated accuracy, and the results are combined to create a final output prediction.

The two most common boosting ensemble machine learning algorithms are:

- AdaBoost
- Stochastic Gradient Boosting

AdaBoost

AdaBoost was the first successful boosting ensemble algorithm. It generally works by weighting instances in the dataset by how easy or difficult they are to classify, allowing the algorithm to pay more or less attention to them in the construction of subsequent models.



You can construct an AdaBoost model for classification using the AdaBoostClassifier class.

The example below demonstrates the construction of 30 decision trees in sequence using the AdaBoost algorithm.

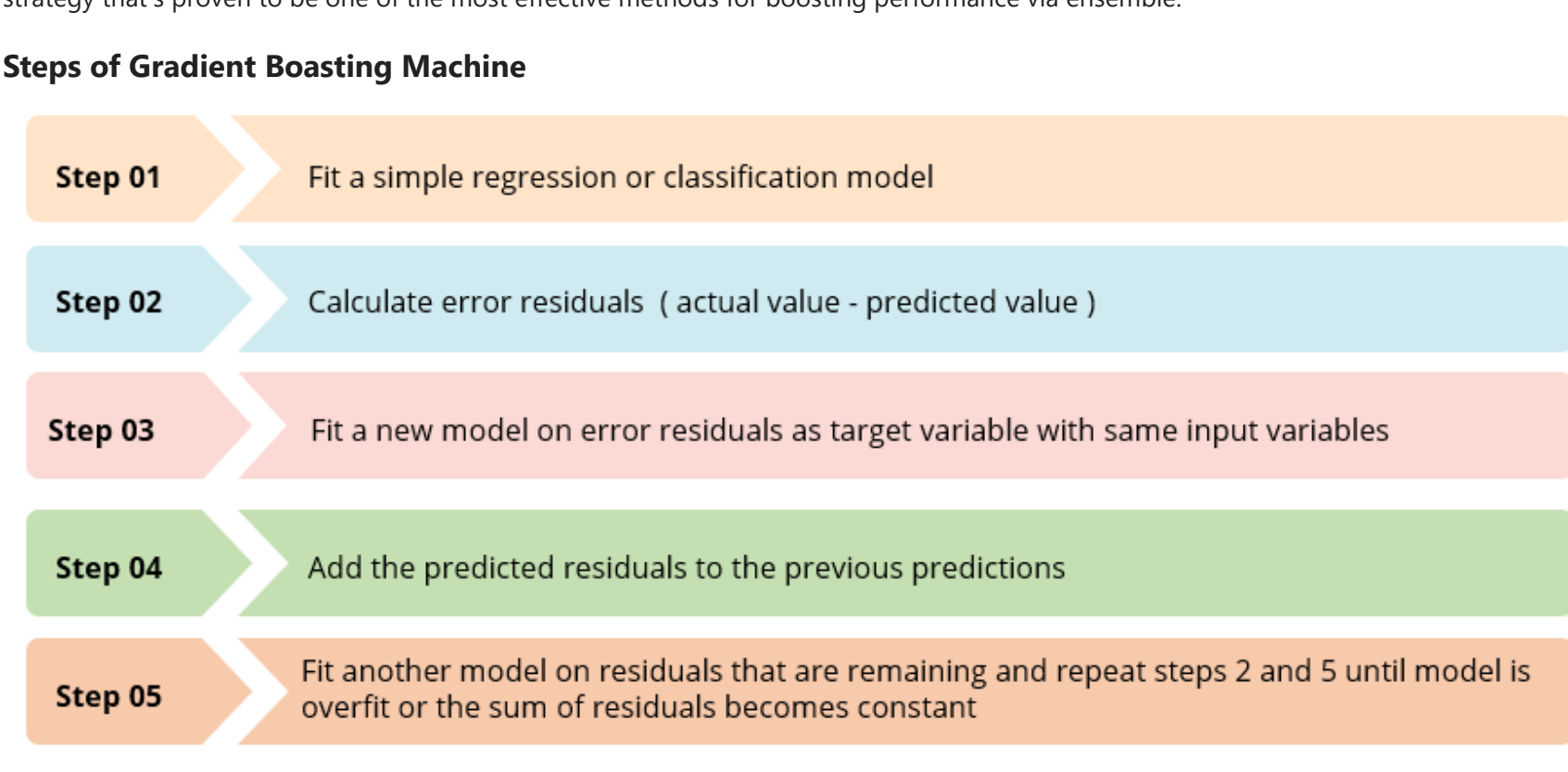
In [74]:
```
#AdaBoost Classification
import pandas
from sklearn import model_selection
from sklearn.ensemble import AdaBoostClassifier

url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']

dataframe = pandas.read_csv(url, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]

seed = 7
num_trees = 30

kfold = model_selection.KFold(n_splits=10, random_state=seed, shuffle=True)
model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)

results = model_selection.cross_val_score(model, X, Y, cv=kfold)
print(results.mean())
```

```
0.7552802460697198
```

Stochastic Gradient Boosting

One of the most advanced ensemble approaches is Stochastic Gradient Boosting (also known as Gradient Boosting Machines). It's also a strategy that's proven to be one of the most effective methods for boosting performance via ensemble.

Steps of Gradient Boasting Machine



You can construct a Gradient Boosting model for classification using the **GradientBoostingClassifier** class.

The example below demonstrates Stochastic Gradient Boosting for classification with 100 trees.

In [75]:
```
#Stochastic Gradient Boosting Classification
import pandas
from sklearn import model_selection
from sklearn.ensemble import GradientBoostingClassifier

url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = pandas.read_csv(url, names=names)

array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
seed = 7
num_trees = 100
kfold = model_selection.KFold(n_splits=10, random_state=seed, shuffle=True)
model = GradientBoostingClassifier(n_estimators=num_trees, random_state=seed)
results = model_selection.cross_val_score(model, X, Y, cv=kfold)
print(results.mean())
```

```
0.7591934381408066
```

CatBoost

CatBoost is an algorithm for gradient boosting on decision trees. It is developed by Yandex researchers and engineers and is used for search, recommendation systems, personal assistants, self-driving cars, weather prediction, and many other tasks at Yandex and in other companies, including CERN, Cloudflare, Careem taxi. It is open-source and can be used by anyone.

Let's study this with the help of a use case.

Data Description

The data consists of real historical data collected from 2010 & 2011. Employees are manually allowed or denied access to resources over time. You must create an algorithm capable of learning from this historical data to predict approval or denial for an unknown set of employees.

File Descriptions

train.csv: It is a training set. Each row has the action (ground truth), resources, and information about the employee's role at the time of approval.

test.csv: It is the test set for which predictions should be made. Each row asks whether an employee having the listed characteristics should have access to the listed resource.

The objective is to develop a model from historical data that will decide the access needs of an employee so that manual access transactions (grants and revocations) are reduced as the attributes of the employee change over time. The model will take information on the position of an employee and a resource code and return whether access should be given or not.

Note: The problem statement is from a Kaggle contest

The objective is to develop a model from historical data, that will decide the access needs of an employee, so that manual access transactions (grants and revocations) are reduced as the attributes of the employee change over time. The model will take information on the position of an employee and a resource code and return whether access should be given or not.
`Note: The problem statement is from a Kaggle contest`

Libraries Installation

In [76]:
```
#Installing CatBoost
!pip install catboost
```

```
Requirement already satisfied: catboost in c:\users\alpika.gupta\anaconda3\lib\site-packages (1.0.6)
Requirement already satisfied: graphviz in c:\users\alpika.gupta\anaconda3\lib\site-packages (from catboost) (0.20.1)
Requirement already satisfied: pandas>=0.24.0 in c:\users\alpika.gupta\anaconda3\lib\site-packages (from catboost) (1.3.4)
Requirement already satisfied: numpy>=1.16.0 in c:\users\alpika.gupta\anaconda3\lib\site-packages (from catboost) (1.20.3)
Requirement already satisfied: scipy in c:\users\alpika.gupta\anaconda3\lib\site-packages (from catboost) (1.7.1)
Requirement already satisfied: six in c:\users\alpika.gupta\anaconda3\lib\site-packages (from catboost) (1.16.0)
Requirement already satisfied: matplotlib in c:\users\alpika.gupta\anaconda3\lib\site-packages (from catboost) (3.4.3)
Requirement already satisfied: plotly in c:\users\alpika.gupta\anaconda3\lib\site-packages (from catboost) (5.8.0)
Requirement already satisfied: pytz>=2017.3 in c:\users\alpika.gupta\anaconda3\lib\site-packages (from pandas>=0.24.0->catboost) (2021.3)
Requirement already satisfied: python-dateutil>=2.7.3 in c:\users\alpika.gupta\anaconda3\lib\site-packages (from pandas>=0.24.0->catboost) (2.8.2)
Requirement already satisfied: cycler>=0.10 in c:\users\alpika.gupta\anaconda3\lib\site-packages (from matplotlib->catboost) (0.10.0)
Requirement already satisfied: pyparsing>=2.2.1 in c:\users\alpika.gupta\anaconda3\lib\site-packages (from matplotlib->catboost) (3.0.4)
Requirement already satisfied: pillow>=6.2.0 in c:\users\alpika.gupta\anaconda3\lib\site-packages (from matplotlib->catboost) (8.4.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\alpika.gupta\anaconda3\lib\site-packages (from matplotlib->catboost) (1.3.1)
Requirement already satisfied: tenacity>=6.2.0 in c:\users\alpika.gupta\anaconda3\lib\site-packages (from plotly->catboost) (8.0.1)
```

In [77]:
```
#To import libraries
import catboost
print(catboost.__version__)
!python --version
```

```
1.0.6
Python 3.9.7
```

Reading the Data

In [78]:
```
#To read the data
import pandas as pd
import os
import numpy as np
np.set_printoptions(precision=4)
import catboost
from catboost import *
from catboost import datasets
```

In [79]:
```
(train_df, test_df) = catboost.datasets.amazon()
```

In [80]:
```
train_df.head()
```

Out[80]:

	ACTION	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPTNAME	ROLE_TITLE	ROLE_FAMILY_DESC	ROLE_FAMILY	ROLE_CO
0	1	39353	85475	117961	118300	123472	117905	117906	290919	1179
1	1	17183	1540	117961	118343	123125	118536	118536	308574	1185
2	1	36724	14457	118219	118220	117884	117879	267952	19721	1178
3	1	36135	5396	117961	118343	119993	118321	240983	290919	1183
4	1	42680	5905	117929	117930	119569	119323	123932	19793	1193

The data will be displayed on the screen.

Preparing Your Data

Label values extraction

Action column contains the categorical feature. However, it is not available for test dataset, so you must drop the Action column.

In [81]:
```
y = train_df.ACTION
X = train_df.drop('ACTION', axis=1)
```

Categorical features declaration

- **cat_features** is a one-dimensional array of categorical columns indices.
- It has one of the following types: list, numpy.ndarray, pandas.DataFrame, and pandas.Series.

Now we will declare the cat feature that holds the categorical values present on train dataset.

In [82]:
```
#The type list is used here
cat_features = list(range(0, X.shape[1]))
print(cat_features)
```

```
[0, 1, 2, 3, 4, 5, 6, 7, 8]
```

In [83]:
```
#looking for label balance in dataset
print('Labels: {}'.format(set(y)))
print('Zero count = {}, One count = {}'.format(len(y) - sum(y), sum(y)))
```

```
Labels: {0, 1}
Zero count = 1897, One count = 30872
```

Ways to create **Pool** class

- In multiprocessing, the Pool class may handle a huge number of processes. It enables you to run several jobs in a single process due to its ability to queue the jobs.

In [84]:
```
#Specifying the dataset
dataset_dir = './amazon'
if not os.path.exists(dataset_dir):
    os.makedirs(dataset_dir)

#We will be able to work with files with/without header and with different separators
train_df.to_csv(
    os.path.join(dataset_dir, 'train.tsv'),
    index=False, sep='\t', header=False
)
test_df.to_csv(
    os.path.join(dataset_dir, 'test.tsv'),
    index=False, sep='\t', header=False
)

train_df.to_csv(
    os.path.join(dataset_dir, 'train.csv'),
    index=False, sep=',', header=True
)
test_df.to_csv(
    os.path.join(dataset_dir, 'test.csv'),
    index=False, sep=',', header=True
)
```

In [85]:
```
!head amazon/train.csv
```

```
'head' is not recognized as an internal or external command,
operable program or batch file.
```

In [86]:
```
from catboost.utils import create_cd
feature_names = dict()
for column, name in enumerate(train_df):
    if column == 0:
        continue
    feature_names[column - 1] = name

create_cd(
    label=0,
    cat_features=list(range(1, train_df.columns.shape[0])),
    feature_names=feature_names,
    output_path=os.path.join(dataset_dir, 'train.cd')
)
```

In [87]:
```
!cat amazon/train.cd
```

```
'cat' is not recognized as an internal or external command,
operable program or batch file.
```

In [88]:
```
pool1 = Pool(data=X, label=y, cat_features=cat_features)
pool2 = Pool(
    data=os.path.join(dataset_dir, 'train.csv'),
    delimiter=',',
    column_description=os.path.join(dataset_dir, 'train.cd'),
    has_header=True
)
pool3 = Pool(data=X, cat_features=cat_features)

#Fastest way to create a Pool is to create it from numpy matrix.
#This way should be used if you want fast predictions
#or fastest way to load the data in python.

X_prepared = X.values.astype(str).astype(object)
#For FeaturesData class categorial features must have type str

pool4 = Pool(
    data=FeaturesData(
        cat_feature_data=X_prepared,
        cat_feature_names=list(X)
    ),
    label=y.values
)

print('Dataset shape')
print('dataset 1:' + str(pool1.shape) +
      '\ndataset 2:' + str(pool2.shape) +
      '\ndataset 3:' + str(pool3.shape) +
      '\ndataset 4: ' + str(pool4.shape))

print('\n')
print('Column names')
print('dataset 1:')
print(pool1.get_feature_names())
print('\ndataset 2:')
print(pool2.get_feature_names())
print('\ndataset 3:')
print(pool3.get_feature_names())
print('\ndataset 4:')
print(pool4.get_feature_names())
```

```
Dataset shape
dataset 1:(32769, 9)
dataset 2:(32769, 9)
dataset 3:(32769, 9)
dataset 4: (32769, 9)


Column names
dataset 1:
['RESOURCE', 'MGR_ID', 'ROLE_ROLLUP_1', 'ROLE_ROLLUP_2', 'ROLE_DEPTNAME', 'ROLE_TITLE', 'ROLE_FAMILY_DESC', 'ROLE_FAMILY', 'ROLE_CODE']

dataset 2:
['RESOURCE', 'MGR_ID', 'ROLE_ROLLUP_1', 'ROLE_ROLLUP_2', 'ROLE_DEPTNAME', 'ROLE_TITLE', 'ROLE_FAMILY_DESC', 'ROLE_FAMILY', 'ROLE_CODE']

dataset 3:
['RESOURCE', 'MGR_ID', 'ROLE_ROLLUP_1', 'ROLE_ROLLUP_2', 'ROLE_DEPTNAME', 'ROLE_TITLE', 'ROLE_FAMILY_DESC', 'ROLE_FAMILY', 'ROLE_CODE']

dataset 4:
['RESOURCE', 'MGR_ID', 'ROLE_ROLLUP_1', 'ROLE_ROLLUP_2', 'ROLE_DEPTNAME', 'ROLE_TITLE', 'ROLE_FAMILY_DESC', 'ROLE_FAMILY', 'ROLE_CODE']
```

Split Your Data into Train and Validation

Let us split the data into **Train** and **Validation**.

In [89]:
```
from sklearn.model_selection import train_test_split
X_train, X_validation, y_train, y_validation = train_test_split(X, y, train_size=0.8, random_state=1234)
```

Selecting the Objective Function

Possible options for binary classification:

`Logloss`

`CrossEntropy` for probabilities in target

A **CatBoostClassifier** trains and applies models for the classification problems. It provides compatibility with the scikit-learn tools.

In [20]:
```
from catboost import CatBoostClassifier
model = CatBoostClassifier(
    iterations=5,
    learning_rate=0.1,
    #loss_function='CrossEntropy'
)
model.fit(
    X_train, y_train,
    cat_features=cat_features,
    eval_set=(X_validation, y_validation),
    verbose=False
)
print('Model is fitted: ' + str(model.is_fitted()))
print('Model params:')
print(model.get_params())
```

```
Model is fitted: True
Model params:
{'iterations': 5, 'learning_rate': 0.1}
```

Stdout of the Training

Stdout displays output directly to the screen console. Output can take any form. It can be output from a print statement, an expression statement, or even a direct prompt.

In [21]:
```
from catboost import CatBoostClassifier
model = CatBoostClassifier(
    iterations=15,
#verbose=5,
)
model.fit(
    X_train, y_train,
    cat_features=cat_features,
    eval_set=(X_validation, y_validation),
)
```

```
Learning rate set to 0.441257
0:      learn: 0.4220777        test: 0.4223741 best: 0.4223741 (0)     total: 33.2ms   remaining: 465ms
1:      learn: 0.3149660        test: 0.3151186 best: 0.3151186 (1)     total: 80.7ms   remaining: 524ms
2:      learn: 0.2621494        test: 0.2629766 best: 0.2629766 (2)     total: 113ms    remaining: 453ms
3:      learn: 0.2302316        test: 0.2302315 best: 0.2302315 (3)     total: 149ms    remaining: 410ms
4:      learn: 0.2060274        test: 0.2019603 best: 0.2019603 (4)     total: 180ms    remaining: 361ms
5:      learn: 0.1956107        test: 0.1894627 best: 0.1894627 (5)     total: 217ms    remaining: 326ms
6:      learn: 0.1870345        test: 0.1790904 best: 0.1790904 (6)     total: 251ms    remaining: 287ms
7:      learn: 0.1836943        test: 0.1748030 best: 0.1748030 (7)     total: 281ms    remaining: 246ms
8:      learn: 0.1807119        test: 0.1707896 best: 0.1707896 (8)     total: 314ms    remaining: 210ms
9:      learn: 0.1775777        test: 0.1662489 best: 0.1662489 (9)     total: 347ms    remaining: 174ms
10:     learn: 0.1762130        test: 0.1654446 best: 0.1654446 (10)    total: 378ms    remaining: 137ms
11:     learn: 0.1760650        test: 0.1653191 best: 0.1653191 (11)    total: 391ms    remaining: 97.8ms
12:     learn: 0.1748232        test: 0.1642093 best: 0.1642093 (12)    total: 425ms    remaining: 65.3ms
13:     learn: 0.1742028        test: 0.1638902 best: 0.1638902 (13)    total: 456ms    remaining: 32.5ms
14:     learn: 0.1733966        test: 0.1627237 best: 0.1627237 (14)    total: 485ms    remaining: 0us

bestTest = 0.162723674
bestIteration = 14
```

Out[21]:
```
<catboost.core.CatBoostClassifier at 0x269b437ea00>
```

Metric Calculation and Graph Plotting

Let us perform metric calculation and graph plotting by importing the **CatBoostClassifier**.

In [22]:
```
from catboost import CatBoostClassifier
model = CatBoostClassifier(
    iterations=50,
    random_seed=63,
    learning_rate=0.5,
    custom_loss=['AUC', 'Accuracy']
)
model.fit(
    X_train, y_train,
    cat_features=cat_features,
    eval_set=(X_validation, y_validation),
    verbose=False,
    plot=True
)
```

Out[22]:
```
<catboost.core.CatBoostClassifier at 0x269b437efd0>
```

Model Comparison

Let us compare the models.

In [23]:
```
model1 = CatBoostClassifier(
    learning_rate=0.7,
    iterations=100,
    random_seed=0,
    train_dir='learing_rate_0.7'
)

model2 = CatBoostClassifier(
    learning_rate=0.01,
    iterations=100,
    random_seed=0,
    train_dir='learing_rate_0.01'
)
model1.fit(
    X_train, y_train,
    eval_set=(X_validation, y_validation),
    cat_features=cat_features,
    verbose=False
)
model2.fit(
    X_train, y_train,
    eval_set=(X_validation, y_validation),
    cat_features=cat_features,
    verbose=False
)
```

Out[23]:
```
<catboost.core.CatBoostClassifier at 0x269b790d550>
```

In [24]:
```
from catboost import MetricVisualizer
MetricVisualizer(['learing_rate_0.01', 'learing_rate_0.7']).start()
```

Best Iteration

In [25]:
```
#Performing best iteration
from catboost import CatBoostClassifier
model = CatBoostClassifier(
    iterations=100,
    random_seed=63,
    learning_rate=0.5,
#use_best_model=False
)
model.fit(
    X_train, y_train,
    cat_features=cat_features,
    eval_set=(X_validation, y_validation),
    verbose=False,
    plot=True
)
```

Out[25]:
```
<catboost.core.CatBoostClassifier at 0x269b45e6a60>
```

In [26]:
```
print('Tree count: ' + str(model.tree_count_))
```

```
Tree count: 82
```

Cross-Validation

Cross-validation is a technique which involves reserving a particular sample of a dataset on which you do not train the model. CatBoost allows to perform cross-validation on the given dataset.

In [27]:
```
#Performing cross-validation
from catboost import cv

params = {}
params['loss_function'] = 'Logloss'
params['iterations'] = 80
params['custom_loss'] = 'AUC'
params['random_seed'] = 63
params['learning_rate'] = 0.5

cv_data = cv(
    params = params,
    pool = Pool(X, label=y, cat_features=cat_features),
    fold_count=5,
    shuffle=True,
    partition_random_seed=0,
    plot=True,
    stratified=False,
    verbose=False
)
```

```
Training on fold [0/5]

bestTest = 0.1695893693
bestIteration = 38

Training on fold [1/5]

bestTest = 0.164632916
bestIteration = 48

Training on fold [2/5]

bestTest = 0.1515742763
bestIteration = 60

Training on fold [3/5]

bestTest = 0.1426916182
bestIteration = 78

Training on fold [4/5]

bestTest = 0.1563234371
bestIteration = 37
```

In [28]:
```
cv_data.head()
```

Out[28]:

	iterations	test-Logloss-mean	test-Logloss-std	train-Logloss-mean	train-Logloss-std	test-AUC-mean	test-AUC-std
0	0	0.302367	0.004317	0.302196	0.004517	0.513577	0.030360
1	1	0.227370	0.007679	0.228497	0.005126	0.642263	0.048004
2	2	0.190856	0.006917	0.196796	0.003999	0.791709	0.011361
3	3	0.178884	0.007455	0.186682	0.003242	0.813889	0.009362
4	4	0.172286	0.007957	0.181380	0.002135	0.826529	0.005319

Logloss is indicative of how close the prediction probability is to the corresponding true value.

Let us print the **Best validation Logloss score**.

```
In [29]:
best_value = np.min(cv_data['test-Logloss-mean'])
best_iter = np.argmin(cv_data['test-Logloss-mean'])

print('Best validation Logloss score, not stratified: {:.4f}±{:.4f} on step {}'.format(
    best_value,
    cv_data['test-Logloss-std'][best_iter],
    best_iter)
)
```

```
Best validation Logloss score, not stratified: 0.1581±0.0104 on step 52
```

```
In [30]:
cv_data = cv(
    params = params,
    pool = Pool(X, label=y, cat_features=cat_features),
    fold_count=5,
    type = 'Classical',
    shuffle=True,
    partition_random_seed=0,
    plot=True,
    stratified=True,
    verbose=False
)

best_value = np.min(cv_data['test-Logloss-mean'])
best_iter = np.argmin(cv_data['test-Logloss-mean'])

print('Best validation Logloss score, stratified: {:.4f}±{:.4f} on step {}'.format(
    best_value,
    cv_data['test-Logloss-std'][best_iter],
    best_iter)
)
```

```
Training on fold [0/5]

bestTest = 0.1614486451
bestIteration = 31

Training on fold [1/5]

bestTest = 0.1554856763
bestIteration = 57

Training on fold [2/5]

bestTest = 0.1588065247
bestIteration = 46

Training on fold [3/5]

bestTest = 0.1525713791
bestIteration = 60

Training on fold [4/5]

bestTest = 0.1576264978
bestIteration = 29

Best validation Logloss score, stratified: 0.1579±0.0036 on step 57
```

Overfitting Detector

If overfitting occurs, CatBoost can stop the training earlier than the training parameters dictate. For example, it can be stopped before the specified number of trees are built. This option is set in the starting parameters.

```
In [31]:
model_with_early_stop = CatBoostClassifier(
    iterations=200,
    random_seed=63,
    learning_rate=0.5,
    early_stopping_rounds=20
)
model_with_early_stop.fit(
    X_train, y_train,
    cat_features=cat_features,
    eval_set=(X_validation, y_validation),
    verbose=False,
    plot=True
)
```

```
Out[31]: <catboost.core.CatBoostClassifier at 0x269b7926460>
```

```
In [32]:
print(model_with_early_stop.tree_count_)
```

```
30
```

```
In [33]:
model_with_early_stop = CatBoostClassifier(
    eval_metric='AUC',
    iterations=200,
    random_seed=63,
    learning_rate=0.5,
    early_stopping_rounds=20
)
model_with_early_stop.fit(
    X_train, y_train,
    cat_features=cat_features,
    eval_set=(X_validation, y_validation),
    verbose=False,
    plot=True
)
```

```
Out[33]: <catboost.core.CatBoostClassifier at 0x269b7926f40>
```

```
In [34]:
print(model_with_early_stop.tree_count_)
```

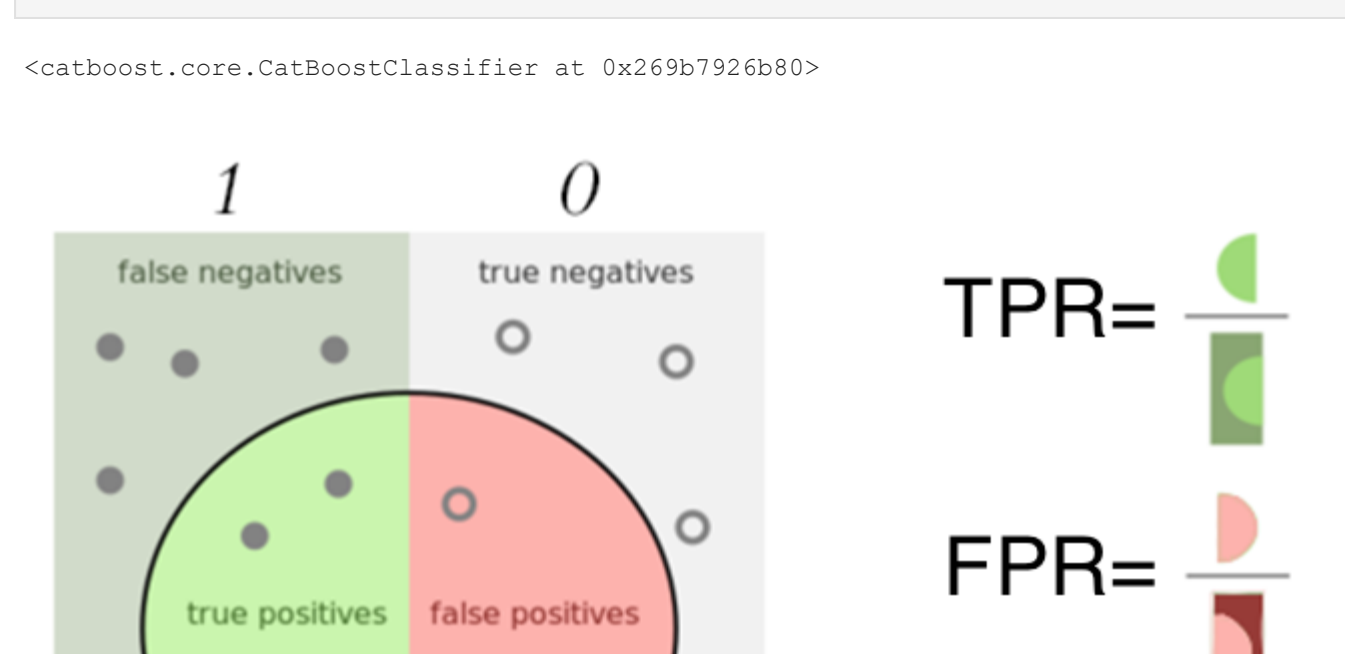
```
30
```

Select Decision Boundary

In classification problems with two or more classes, a decision boundary is a hypersurface that separates the underlying vector space into sets, keeping one for each class.

```
In [35]:
model = CatBoostClassifier(
    random_seed=63,
    iterations=200,
    learning_rate=0.03,
)
model.fit(
    X_train, y_train,
    cat_features=cat_features,
    verbose=False,
    plot=True
)
```

```
Out[35]: <catboost.core.CatBoostClassifier at 0x269b7926b80>
```



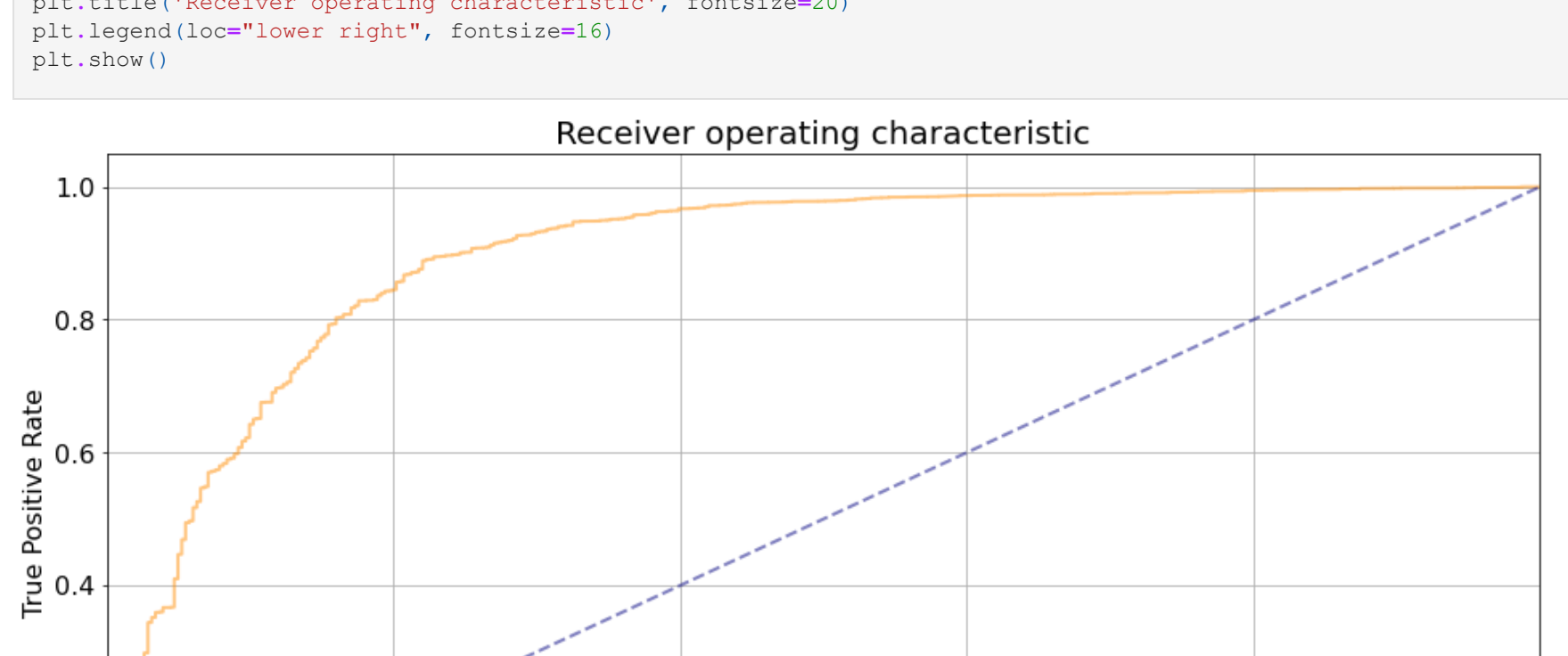

```
In [36]:
#Using utils to make the pattern easier
from catboost.utils import get_roc_curve
import sklearn
from sklearn import metrics

eval_pool = Pool(X_validation, y_validation, cat_features=cat_features)
curve = get_roc_curve(model, eval_pool)
(fpr, tpr, thresholds) = curve
roc_auc = sklearn.metrics.auc(fpr, tpr)
```

```
In [37]:
import matplotlib.pyplot as plt

plt.figure(figsize=(16, 8))
lw = 2

plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve (area = %0.2f)' % roc_auc, alpha=0.5)

plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--', alpha=0.5)

plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.grid(True)
plt.xlabel('False Positive Rate', fontsize=16)
plt.ylabel('True Positive Rate', fontsize=16)
plt.title('Receiver operating characteristic', fontsize=20)
plt.legend(loc="lower right", fontsize=16)
plt.show()
```

The above graph illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.

```
In [38]:
from catboost.utils import get_fpr_curve
from catboost.utils import get_fnr_curve

(thresholds, fpr) = get_fpr_curve(curve=curve)
(thresholds, fnr) = get_fnr_curve(curve=curve)
```

```
In [39]:
plt.figure(figsize=(16, 8))
lw = 2

plt.plot(thresholds, fpr, color='blue', lw=lw, label='FPR', alpha=0.5)
plt.plot(thresholds, fnr, color='green', lw=lw, label='FNR', alpha=0.5)

plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.grid(True)
plt.xlabel('Threshold', fontsize=16)
plt.ylabel('Error Rate', fontsize=16)
plt.title('FPR-FNR curves', fontsize=20)
plt.legend(loc="lower left", fontsize=16)
plt.show()
```



The above graph displays the FPR-FNR curves for error rate and threshold.

```
In [40]:
from catboost.utils import select_threshold

print(select_threshold(model=model, data=eval_pool, FNR=0.01))
print(select_threshold(model=model, data=eval_pool, FPR=0.01))
```

```
0.48034745289964775
0.9899643475743053
```

Snapshotting

Catboost supports snapshotting. You can use it to recover training after an interruption or start training with previous results.

```
In [41]:
#!rm 'catboost_info/snapshot.bkp'
from catboost import CatBoostClassifier
model = CatBoostClassifier(
    iterations=100,
    save_snapshot=True,
    snapshot_file='snapshot.bkp',
    snapshot_interval=1,
    random_seed=43
)
model.fit(
    X_train, y_train,
    eval_set=(X_validation, y_validation),
    cat_features=cat_features,
    verbose=True
)
```

```
Learning rate set to 0.193326
0:	learn: 0.5565905	test: 0.5566217 best: 0.5566217 (0)	total: 17.3ms	remaining: 1.71s
1:	learn: 0.4642626	test: 0.4639935 best: 0.4639935 (1)	total: 51ms	remaining: 2.5s
2:	learn: 0.3989148	test: 0.3981304 best: 0.3981304 (2)	total: 79.1ms	remaining: 2.56s
3:	learn: 0.3516186	test: 0.3510286 best: 0.3510286 (3)	total: 92.4ms	remaining: 2.22s
4:	learn: 0.3164302	test: 0.3161297 best: 0.3161297 (4)	total: 124ms	remaining: 2.35s
5:	learn: 0.2906047	test: 0.2905494 best: 0.2905494 (5)	total: 134ms	remaining: 2.09s
6:	learn: 0.2710475	test: 0.2708899 best: 0.2708899 (6)	total: 157ms	remaining: 2.09s
7:	learn: 0.2538458	test: 0.2539798 best: 0.2539798 (7)	total: 194ms	remaining: 2.23s
8:	learn: 0.2399269	test: 0.2401350 best: 0.2401350 (8)	total: 237ms	remaining: 2.4s
9:	learn: 0.2298664	test: 0.2304173 best: 0.2304173 (9)	total: 271ms	remaining: 2.44s
10:	learn: 0.2180381	test: 0.2161946 best: 0.2161946 (10)	total: 303ms	remaining: 2.45s
11:	learn: 0.2089276	test: 0.2055572 best: 0.2055572 (11)	total: 336ms	remaining: 2.46s
12:	learn: 0.2027605	test: 0.1985313 best: 0.1985313 (12)	total: 361ms	remaining: 2.42s
13:	learn: 0.1980597	test: 0.1929079 best: 0.1929079 (13)	total: 395ms	remaining: 2.42s
14:	learn: 0.1931802	test: 0.1869335 best: 0.1869335 (14)	total: 430ms	remaining: 2.44s
15:	learn: 0.1899584	test: 0.1827767 best: 0.1827767 (15)	total: 475ms	remaining: 2.49s
16:	learn: 0.1868109	test: 0.1791481 best: 0.1791481 (16)	total: 510ms	remaining: 2.49s
17:	learn: 0.1844046	test: 0.1764212 best: 0.1764212 (17)	total: 544ms	remaining: 2.48s
18:	learn: 0.1826815	test: 0.1739992 best: 0.1739992 (18)	total: 576ms	remaining: 2.45s
19:	learn: 0.1813182	test: 0.1724242 best: 0.1724242 (19)	total: 608ms	remaining: 2.43s
20:	learn: 0.1799044	test: 0.1705979 best: 0.1705979 (20)	total: 648ms	remaining: 2.44s
21:	learn: 0.1787567	test: 0.1691593 best: 0.1691593 (21)	total: 699ms	remaining: 2.48s
22:	learn: 0.1778479	test: 0.1679138 best: 0.1679138 (22)	total: 732ms	remaining: 2.45s
23:	learn: 0.1769800	test: 0.1669261 best: 0.1669261 (23)	total: 772ms	remaining: 2.44s
24:	learn: 0.1761963	test: 0.1659238 best: 0.1659238 (24)	total: 822ms	remaining: 2.47s
25:	learn: 0.1759394	test: 0.1656044 best: 0.1656044 (25)	total: 842ms	remaining: 2.4s
26:	learn: 0.1756321	test: 0.1651183 best: 0.1651183 (26)	total: 881ms	remaining: 2.38s
27:	learn: 0.1753093	test: 0.1645482 best: 0.1645482 (27)	total: 913ms	remaining: 2.35s
28:	learn: 0.1746490	test: 0.1634569 best: 0.1634569 (28)	total: 949ms	remaining: 2.32s
29:	learn: 0.1741248	test: 0.1626719 best: 0.1626719 (29)	total: 984ms	remaining: 2.3s
30:	learn: 0.1739190	test: 0.1624505 best: 0.1624505 (30)	total: 1.02s	remaining: 2.27s
31:	learn: 0.1737505	test: 0.1621577 best: 0.1621577 (31)	total: 1.08s	remaining: 2.29s
32:	learn: 0.1735156	test: 0.1617652 best: 0.1617652 (32)	total: 1.12s	remaining: 2.27s
33:	learn: 0.1733737	test: 0.1616706 best: 0.1616706 (33)	total: 1.17s	remaining: 2.27s
34:	learn: 0.1730710	test: 0.1615700 best: 0.1615700 (34)	total: 1.21s	remaining: 2.24s
35:	learn: 0.1726234	test: 0.1613597 best: 0.1613597 (35)	total: 1.24s	remaining: 2.21s
36:	learn: 0.1724223	test: 0.1609771 best: 0.1609771 (36)	total: 1.28s	remaining: 2.18s
37:	learn: 0.1723166	test: 0.1609138 best: 0.1609138 (37)	total: 1.31s	remaining: 2.14s
38:	learn: 0.1721109	test: 0.1607760 best: 0.1607760 (38)	total: 1.35s	remaining: 2.11s
39:	learn: 0.1718253	test: 0.1604844 best: 0.1604844 (39)	total: 1.38s	remaining: 2.07s
40:	learn: 0.1718135	test: 0.1604838 best: 0.1604838 (40)	total: 1.41s	remaining: 2.03s
41:	learn: 0.1717654	test: 0.1604337 best: 0.1604337 (41)	total: 1.46s	remaining: 2.02s
42:	learn: 0.1714937	test: 0.1602021 best: 0.1602021 (42)	total: 1.51s	remaining: 2s
43:	learn: 0.1713759	test: 0.1601088 best: 0.1601088 (43)	total: 1.54s	remaining: 1.96s
44:	learn: 0.1712930	test: 0.1601280 best: 0.1601088 (43)	total: 1.57s	remaining: 1.92s
45:	learn: 0.1710363	test: 0.1601333 best: 0.1601088 (43)	total: 1.61s	remaining: 1.89s
46:	learn: 0.1708310	test: 0.1598021 best: 0.1598021 (46)	total: 1.66s	remaining: 1.87s
47:	learn: 0.1707415	test: 0.1598379 best: 0.1598021 (46)	total: 1.69s	remaining: 1.84s
48:	learn: 0.1706194	test: 0.1597803 best: 0.1597803 (48)	total: 1.73s	remaining: 1.8s
49:	learn: 0.1705094	test: 0.1598181 best: 0.1597803 (48)	total: 1.77s	remaining: 1.77s
50:	learn: 0.1703454	test: 0.1596611 best: 0.1596611 (50)	total: 1.81s	remaining: 1.74s
51:	learn: 0.1701364	test: 0.1594569 best: 0.1594569 (51)	total: 1.86s	remaining: 1.71s
52:	learn: 0.1699351	test: 0.1594792 best: 0.1594569 (51)	total: 1.89s	remaining: 1.68s
53:	learn: 0.1698191	test: 0.1594453 best: 0.1594453 (53)	total: 1.93s	remaining: 1.65s
54:	learn: 0.1696360	test: 0.1594233 best: 0.1594233 (54)	total: 1.97s	remaining: 1.61s
55:	learn: 0.1695476	test: 0.1593201 best: 0.1593201 (55)	total: 2.02s	remaining: 1.59s
56:	learn: 0.1694507	test: 0.1593702 best: 0.1593201 (55)	total: 2.05s	remaining: 1.55s
57:	learn: 0.1693879	test: 0.1593558 best: 0.1593201 (55)	total: 2.1s	remaining: 1.52s
58:	learn: 0.1692182	test: 0.1593365 best: 0.1593201 (55)	total: 2.14s	remaining: 1.49s
59:	learn: 0.1691692	test: 0.1593046 best: 0.1593046 (59)	total: 2.17s	remaining: 1.45s
60:	learn: 0.1689825	test: 0.1590959 best: 0.1590959 (60)	total: 2.2s	remaining: 1.41s
61:	learn: 0.1688233	test: 0.1587949 best: 0.1587949 (61)	total: 2.24s	remaining: 1.37s
62:	learn: 0.1687423	test: 0.1587121 best: 0.1587121 (62)	total: 2.28s	remaining: 1.34s
63:	learn: 0.1685821	test: 0.1585367 best: 0.1585367 (63)	total: 2.31s	remaining: 1.3s
64:	learn: 0.1682095	test: 0.1583598 best: 0.1583598 (64)	total: 2.35s	remaining: 1.27s
65:	learn: 0.1680435	test: 0.1581916 best: 0.1581916 (65)	total: 2.39s	remaining: 1.23s
66:	learn: 0.1678092	test: 0.1580685 best: 0.1580685 (66)	total: 2.42s	remaining: 1.19s
67:	learn: 0.1676905	test: 0.1579741 best: 0.1579741 (67)	total: 2.45s	remaining: 1.16s
68:	learn: 0.1674648	test: 0.1579143 best: 0.1579143 (68)	total: 2.49s	remaining: 1.12s
69:	learn: 0.1673214	test: 0.1579064 best: 0.1579064 (69)	total: 2.53s	remaining: 1.08s
70:	learn: 0.1672664	test: 0.1579522 best: 0.1579064 (69)	total: 2.57s	remaining: 1.05s
71:	learn: 0.1672555	test: 0.1579174 best: 0.1579064 (69)	total: 2.63s	remaining: 1.02s
72:	learn: 0.1672462	test: 0.1579299 best: 0.1579064 (69)	total: 2.69s	remaining: 996ms
73:	learn: 0.1670767	test: 0.1578301 best: 0.1578301 (73)	total: 2.73s	remaining: 958ms
74:	learn: 0.1670546	test: 0.1577969 best: 0.1577969 (74)	total: 2.76s	remaining: 920ms
75:	learn: 0.1669987	test: 0.1577948 best: 0.1577948 (75)	total: 2.8s	remaining: 885ms
76:	learn: 0.1668860	test: 0.1577237 best: 0.1577237 (76)	total: 2.84s	remaining: 847ms
77:	learn: 0.1667215	test: 0.1576140 best: 0.1576140 (77)	total: 2.9s	remaining: 818ms
78:	learn: 0.1667140	test: 0.1575968 best: 0.1575968 (78)	total: 2.94s	remaining: 781ms
79:	learn: 0.1666534	test: 0.1575803 best: 0.1575803 (79)	total: 2.99s	remaining: 748ms
80:	learn: 0.1666215	test: 0.1575678 best: 0.1575678 (80)	total: 3.03s	remaining: 710ms
81:	learn: 0.1665369	test: 0.1576578 best: 0.1575678 (80)	total: 3.06s	remaining: 673ms
82:	learn: 0.1664881	test: 0.1576933 best: 0.1575678 (80)	total: 3.11s	remaining: 638ms
83:	learn: 0.1664809	test: 0.1576931 best: 0.1575678 (80)	total: 3.16s	remaining: 602ms
84:	learn: 0.1664459	test: 0.1577250 best: 0.1575678 (80)	total: 3.21s	remaining: 566ms
85:	learn: 0.1664193	test: 0.1577061 best: 0.1575678 (80)	total: 3.24s	remaining: 528ms
86:	learn: 0.1663895	test: 0.1577540 best: 0.1575678 (80)	total: 3.29s	remaining: 491ms
87:	learn: 0.1663837	test: 0.1577521 best: 0.1575678 (80)	total: 3.32s	remaining: 453ms
88:	learn: 0.1663628	test: 0.1577793 best: 0.1575678 (80)	total: 3.36s	remaining: 416ms
89:	learn: 0.1663101	test: 0.1577507 best: 0.1575678 (80)	total: 3.4s	remaining: 378ms
90:	learn: 0.1662302	test: 0.1576135 best: 0.1575678 (80)	total: 3.44s	remaining: 340ms
91:	learn: 0.1662257	test: 0.1576185 best: 0.1575678 (80)	total: 3.47s	remaining: 302ms
92:	learn: 0.1662070	test: 0.1576770 best: 0.1575678 (80)	total: 3.52s	remaining: 265ms
93:	learn: 0.1661519	test: 0.1576925 best: 0.1575678 (80)	total: 3.57s	remaining: 228ms
94:	learn: 0.1659885	test: 0.1576700 best: 0.1575678 (80)	total: 3.62s	remaining: 190ms
95:	learn: 0.1659752	test: 0.1577138 best: 0.1575678 (80)	total: 3.66s	remaining: 153ms
96:	learn: 0.1658729	test: 0.1577104 best: 0.1575678 (80)	total: 3.7s	remaining: 114ms
97:	learn: 0.1658312	test: 0.1577005 best: 0.1575678 (80)	total: 3.73s	remaining: 76.2ms
98:	learn: 0.1657567	test: 0.1576310 best: 0.1575678 (80)	total: 3.77s	remaining: 38.1ms
99:	learn: 0.1655047	test: 0.1576241 best: 0.1575678 (80)	total: 3.81s	remaining: 0us

bestTest = 0.1575677776
bestIteration = 80

Shrink model to first 81 iterations.
Out[41]: <catboost.core.CatBoostClassifier at 0x269c0f10700>
```

Model Predictions

predict_proba gives you the probabilities for the target in array form. The number of probabilities for each row is equal to the number of categories in the target variable.

```
In [42]:
print(model.predict_proba(X=X_validation))
```

```
[[0.0508 0.9492]
 [0.0181 0.9819]
 [0.0179 0.9821]
 ...
 [0.0161 0.9839]
 [0.017  0.983 ]
 [0.0236 0.9764]]
```

```
In [43]:
print(model.predict(data=X_validation))
```

```
[1 1 1 ... 1 1 1]
```

```
In [44]:
raw_pred = model.predict(
    data=X_validation,
    prediction_type='RawFormulaVal'
)
print(raw_pred)
```

```
[2.9282 3.9947 4.0077 ... 4.1115 4.06   3.7207]
```

```
In [45]:
from numpy import exp

#Calculating sigmoid
sigmoid = lambda x: 1 / (1 + exp(-x))

probabilities = sigmoid(raw_pred)

print(probabilities)
```

```
[0.9492 0.9819 0.9821 ... 0.9839 0.983  0.9764]
```

The probabilities will be displayed on the screen.

```
In [46]:
X_prepared = X_validation.values.astype(str).astype(object)
#For FeaturesData class categorial features must have type str

fast_predictions = model.predict_proba(
    X=FeaturesData(
        cat_feature_data=X_prepared,
        cat_feature_names=list(X_validation)
    )
)
print(fast_predictions)
```

```
[[0.0508 0.9492]
 [0.0181 0.9819]
 [0.0179 0.9821]
 ...
 [0.0161 0.9839]
 [0.017  0.983 ]
 [0.0236 0.9764]]
```

Staged Prediction

CatBoost allows to apply a trained model and calculate the results for each i-th tree of the model, taking into consideration only the trees in the range [0; i).

```
In [47]:
predictions_gen = model.staged_predict_proba(
    data=X_validation,
    ntree_start=0,
    ntree_end=5,
    eval_period=1
)
try:
    for iteration, predictions in enumerate(predictions_gen):
        print('Iteration ' + str(iteration) + ', predictions:')
        print(predictions)
except Exception:
    pass
```

```
Iteration 0, predictions:
[[0.4154 0.5846]
 [0.4154 0.5846]
 [0.4154 0.5846]
 ...
 [0.4154 0.5846]
 [0.4154 0.5846]
 [0.4154 0.5846]]
Iteration 1, predictions:
[[0.3476 0.6524]
 [0.3476 0.6524]
 [0.3476 0.6524]
 ...
 [0.3476 0.6524]
 [0.3476 0.6524]
 [0.3476 0.6524]]
Iteration 2, predictions:
[[0.292  0.708 ]
 [0.292  0.708 ]
 [0.2978 0.7022]
 ...
 [0.2978 0.7022]
 [0.292  0.708 ]
 [0.2978 0.7022]]
Iteration 3, predictions:
[[0.2485 0.7515]
 [0.2485 0.7515]
 [0.2538 0.7462]
 ...
 [0.2538 0.7462]
 [0.2485 0.7515]
 [0.2538 0.7462]]
Iteration 4, predictions:
[[0.2126 0.7874]
 [0.2126 0.7874]
 [0.2173 0.7827]
 ...
 [0.2173 0.7827]
 [0.2126 0.7874]
 [0.2173 0.7827]]
```

Solving Multiclass Classification Problem

Let us solve the **Multiclass Classification Problem** using the **CatBoostClassifier.**

```
In [48]:
from catboost import CatBoostClassifier
model = CatBoostClassifier(
    iterations=50,
    random_seed=43,
    loss_function='MultiClass'
)
model.fit(
    X_train, y_train,
    cat_features=cat_features,
    eval_set=(X_validation, y_validation),
    verbose=False,
    plot=True
)
```

```
Out[48]: <catboost.core.CatBoostClassifier at 0x269b7ad3dc0>
```

For multiclass problems with many classes, sometimes, it's better to solve classification problems using ranking. To do that, we will build a dataset with groups. Every group will represent one object from our initial dataset. But it will have one additional categorical feature, a possible class value. Target values will be equal to 1 if the class value is equal to the correct class and 0 otherwise. Thus, each group will have exactly one 1 in labels and some zeros. You can put all possible class values in the group, or you can try setting only hard negatives if there are too many labels. We'll show this approach as an example of a binary classification problem.

```
In [49]:
#Defining custom function to build multiclass ranking
from copy import deepcopy
def build_multiclass_ranking_dataset(X, y, cat_features, label_values=[0,1], start_group_id=0):
    ranking_matrix = []
    ranking_labels = []
    group_ids = []

    X_train_matrix = X.values
    y_train_vector = y.values

    for obj_idx in range(X.shape[0]):
        obj = list(X_train_matrix[obj_idx])

        for label in label_values:
            obj_of_given_class = deepcopy(obj)
            obj_of_given_class.append(label)
            ranking_matrix.append(obj_of_given_class)
            ranking_labels.append(float(y_train_vector[obj_idx] == label))
            group_ids.append(start_group_id + obj_idx)

    final_cat_features = deepcopy(cat_features)
    final_cat_features.append(X.shape[1]) # new feature that we are adding should be categorical.
    return Pool(ranking_matrix, ranking_labels, cat_features=final_cat_features, group_id = group_ids)
```

```
In [50]:
from catboost import CatBoost
params = {'iterations':150, 'learning_rate':0.01, 'l2_leaf_reg':30, 'random_seed':0,
          'loss_function':'QuerySoftMax'}

groupwise_train_pool = build_multiclass_ranking_dataset(X_train, y_train, cat_features, [0,1])
groupwise_eval_pool = build_multiclass_ranking_dataset(X_validation, y_validation, cat_features,
                                                        [0,1], X_train.shape[0])

model = CatBoost(params)
model.fit(
    X=groupwise_train_pool,
    verbose=False,
    eval_set=groupwise_eval_pool,
    plot=True
)
```

```
Out[50]: <catboost.core.CatBoost at 0x269af65cd90>
```

Making predictions with ranking mode

```
In [51]:
import math

obj = list(X_validation.values[0])
ratings = []
for label in [0,1]:
    obj_with_label = deepcopy(obj)
    obj_with_label.append(label)
    rating = model.predict([obj_with_label])[0]
    ratings.append(rating)
print('Raw values:', np.array(ratings))

def soft_max(values):
    return [math.exp(val) / sum([math.exp(val) for val in values]) for val in values]

print('Probabilities', np.array(soft_max(ratings)))
```

```
Raw values: [-0.471   0.4713]
Probabilities [0.2804 0.7196]
```

Metric Evaluation on a New Dataset

Let us perform **Metric Evaluation** on a new dataset using the training data.

```
In [52]:
model = CatBoostClassifier(
    random_seed=63,
    iterations=200,
    learning_rate=0.03,
)
model.fit(
    X_train, y_train,
    cat_features=cat_features,
    verbose=50
)
```

```
0:	learn: 0.6569860	total: 31.6ms	remaining: 6.28s
50:	learn: 0.1907871	total: 2.33s	remaining: 6.82s
100:	learn: 0.1645125	total: 5.13s	remaining: 5.03s
150:	learn: 0.1565519	total: 8.4s	remaining: 2.73s
199:	learn: 0.1533854	total: 11.7s	remaining: 0us
Out[52]: <catboost.core.CatBoostClassifier at 0x269b4608a30>
```

```
In [53]:
metrics = model.eval_metrics(
    data=pool1,
    metrics=['Logloss','AUC'],
    ntree_start=0,
    ntree_end=0,
    eval_period=1,
    plot=True
)
```

```
In [54]:
print('AUC values:')
print(np.array(metrics['AUC']))
```

```
AUC values:
[0.4998 0.538  0.5504 0.5888 0.6536 0.6515 0.6476 0.648  0.7117 0.731
 0.7277 0.7278 0.7299 0.7298 0.7275 0.7273 0.7336 0.735  0.7445 0.7606
 0.7627 0.7627 0.7715 0.7699 0.7773 0.7824 0.7859 0.8067 0.818  0.846
 0.8607 0.8651 0.874  0.8745 0.8797 0.8794 0.8964 0.8969 0.9042 0.9129
 0.9154 0.916  0.9175 0.9197 0.9245 0.9253 0.9301 0.9298 0.9305 0.931
 0.9316 0.9332 0.9333 0.9356 0.9361 0.938  0.9393 0.9392 0.9395 0.941
 0.9417 0.9431 0.9433 0.9436 0.944  0.9452 0.9458 0.9458 0.9479 0.9492
 0.9503 0.9509 0.9517 0.9527 0.9537 0.9541 0.955  0.9556 0.9559 0.9564
 0.9574 0.958  0.9591 0.9598 0.9602 0.9606 0.961  0.9615 0.9621 0.9625
 0.9629 0.9635 0.9641 0.9644 0.9646 0.965  0.9654 0.9657 0.9659 0.966
 0.9662 0.9666 0.9668 0.9669 0.9673 0.9675 0.9677 0.9678 0.9679 0.9679
 0.9681 0.9682 0.9682 0.9683 0.9684 0.9685 0.9686 0.9687 0.9687 0.9688
 0.9688 0.9689 0.9689 0.9691 0.9692 0.9693 0.9693 0.9694 0.9694 0.9693
 0.9694 0.9699 0.9704 0.9708 0.9712 0.9716 0.972  0.9721 0.9724 0.9724
 0.9728 0.9731 0.9733 0.9736 0.9738 0.9738 0.9739 0.974  0.974  0.9742
 0.9741 0.9744 0.9746 0.975  0.9751 0.9754 0.9756 0.9755 0.9759 0.9759
 0.9762 0.9765 0.9765 0.9766 0.9767 0.9767 0.9768 0.9771 0.9771 0.9771
 0.9772 0.9773 0.9775 0.9777 0.9777 0.9778 0.9779 0.9779 0.9779 0.9779
 0.9779 0.9779 0.9779 0.9779 0.978  0.978  0.978  0.978  0.978  0.978
 0.978  0.9783 0.9785 0.9785 0.9785 0.9785 0.9785 0.9785 0.9787 0.9788]
```

Feature Importances

Feature importance refers to techniques that assign a score to input features based on how useful they are at predicting a target variable.

```
In [55]:
#To find feature importance
model.get_feature_importance(prettified=True)
```

Out[55]:

	Feature Id	Importances
0	RESOURCE	22.311819
1	MGR_ID	18.121045
2	ROLE_DEPTNAME	14.891573
3	ROLE_ROLLUP_2	12.310360
4	ROLE_CODE	10.388989
5	ROLE_FAMILY_DESC	9.144182
6	ROLE_TITLE	6.402628
7	ROLE_FAMILY	4.649123
8	ROLE_ROLLUP_1	1.780282

Scores are assigned to the input features.

Feature Evaluation

Let us perform feature evaluation using the **eval_features( )** function.

```
In [56]:
from catboost.eval.catboost_evaluation import *
learn_params = {'iterations': 20, # 2000
                'learning_rate': 0.5, #we set big learning_rate, because we have small iterations
                'random_seed': 0,
                'verbose': False,
                'loss_function' : 'Logloss',
                'boosting_type': 'Plain'}
evaluator = CatboostEvaluation('amazon/train.tsv',
                               fold_size=10000, #<= 50% of dataset
                               fold_count=20,
                               column_description='amazon/train.cd',
                               partition_random_seed=0,
                               #working_dir=...
)
result = evaluator.eval_features(learn_config=learn_params,
                                 eval_metrics=['Logloss', 'Accuracy'],
                                 features_to_eval=[6, 7, 8])
```

```
In [57]:
from catboost.eval.evaluation_result import *
logloss_result = result.get_metric_results('Logloss')
logloss_result.get_baseline_comparison(
    ScoreConfig(ScoreType.Rel, overfit_iterations_info=False)
)
```

Out[57]:

	PValue	Score	Quantile 0.005	Quantile 0.995	Decision
Features: 6	0.000189	1.010962	0.586856	1.396997	GOOD
Features: 7	0.681322	-0.033237	-0.316979	0.280699	UNKNOWN
Features: 8	0.005111	-0.439271	-0.812376	-0.114295	BAD

Saving the Model

```
In [58]:
my_best_model = CatBoostClassifier(iterations=10)
my_best_model.fit(
    X_train, y_train,
    eval_set=(X_validation, y_validation),
    cat_features=cat_features,
    verbose=False
)
my_best_model.save_model('catboost_model.bin')
my_best_model.save_model('catboost_model.json', format='json')
```

```
In [59]:
my_best_model.load_model('catboost_model.bin')
print(my_best_model.get_params())
print(my_best_model.random_seed_)
```

```
{'iterations': 10, 'loss_function': 'Logloss', 'verbose': 0}
0
```

Hyperparameter Tunning

Hyperparameter tuning is the process of determining the right combination of hyperparameters that allows the model to maximize model performance. Setting the correct combination of hyperparameters is the only way to extract the maximum performance out of models.

Training Speed

```
In [60]:
from catboost import CatBoost
fast_model = CatBoostClassifier(
    random_seed=63,
    iterations=150,
    learning_rate=0.01,
    boosting_type='Plain',
    bootstrap_type='Bernoulli',
    subsample=0.5,
    one_hot_max_size=20,
    rsm=0.5,
    leaf_estimation_iterations=5,
    max_ctr_complexity=1)

fast_model.fit(
    X_train, y_train,
    cat_features=cat_features,
    verbose=False,
    plot=True
)
```

```
Out[60]: <catboost.core.CatBoostClassifier at 0x269b5f76400>
```

Accuracy

```
In [61]:
tunned_model = CatBoostClassifier(
    random_seed=63,
    iterations=1000,
    learning_rate=0.03,
    l2_leaf_reg=3,
    bagging_temperature=1,
    random_strength=1,
    one_hot_max_size=2,
    leaf_estimation_method='Newton'
)
tunned_model.fit(
    X_train, y_train,
    cat_features=cat_features,
    verbose=False,
    eval_set=(X_validation, y_validation),
    plot=True
)
```

```
Out[61]: <catboost.core.CatBoostClassifier at 0x269b4b12430>
```

Training the Model after Parameter Tuning

```
In [62]:
best_model = CatBoostClassifier(
    random_seed=63,
    iterations=int(tunned_model.tree_count_ * 1.2),
)
best_model.fit(
    X, y,
    cat_features=cat_features,
    verbose=100
)
```

```
Learning rate set to 0.040343
0:	learn: 0.6456466	total: 28.3ms	remaining: 32.4s
100:	learn: 0.1534434	total: 6.59s	remaining: 1m 8s
200:	learn: 0.1466718	total: 14.5s	remaining: 1m 8s
300:	learn: 0.1430361	total: 22.6s	remaining: 1m 3s
400:	learn: 0.1399976	total: 31.1s	remaining: 57.8s
500:	learn: 0.1372704	total: 40.6s	remaining: 52.3s
600:	learn: 0.1341051	total: 49.8s	remaining: 45.1s
700:	learn: 0.1313257	total: 59.1s	remaining: 37.5s
800:	learn: 0.1285775	total: 1m 7s	remaining: 29.2s
900:	learn: 0.1263064	total: 1m 16s	remaining: 20.7s
1000:	learn: 0.1238298	total: 1m 25s	remaining: 12.3s
1100:	learn: 0.1212612	total: 1m 33s	remaining: 3.84s
1145:	learn: 0.1202083	total: 1m 37s	remaining: 0us
Out[62]: <catboost.core.CatBoostClassifier at 0x269be0f3fd0>
```

Calculate Prediction

```
In [63]:
#Let us calculate contest predictions
X_test = test_df.drop('id', axis=1)
test_pool = Pool(data=X_test, cat_features=cat_features)
contest_predictions = best_model.predict_proba(test_pool)
print('Predictions:')
print(contest_predictions)
```

```
Predictions:
[[0.4455 0.5545]
 [0.0133 0.9867]
 [0.0116 0.9884]
 ...
 [0.0054 0.9946]
 [0.0422 0.9578]
 [0.0117 0.9883]]
```

Voting Ensemble

Voting is one of the simplest ways of combining the predictions from multiple machine learning algorithms.

It works by first creating two or more standalone models from your training dataset. A Voting Classifier can then be used to wrap your models and average the predictions of the submodels when asked to make predictions for new data.

The predictions of the submodels can be weighted, but specifying the weights for classifiers manually or even heuristically is difficult. More advanced methods can learn how to best weight the predictions from submodels, but this is called stacking (stacked generalization) and is currently not provided in scikit-learn.

You can create a voting ensemble model for classification using the **VotingClassifier** class.

The code below provides an example of combining the predictions of logistic regression, classification, and regression trees and support vector machines together for a classification problem.

In [64]:

```python
#Voting Ensemble for Classification
import pandas
from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import VotingClassifier

url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = pandas.read_csv(url, names=names)

array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
seed = 7
kfold = model_selection.KFold(n_splits=10)

#Create the sub models
estimators = []
model1 = LogisticRegression()
estimators.append(('logistic', model1))
model2 = DecisionTreeClassifier()
estimators.append(('cart', model2))
model3 = SVC()
estimators.append(('svm', model3))

#Create the ensemble model
ensemble = VotingClassifier(estimators)
results = model_selection.cross_val_score(ensemble, X, Y, cv=kfold)
print(results.mean())
```

```
C:\Users\alpika.gupta\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:444: ConvergenceWarning: lb
fgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\alpika.gupta\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:444: ConvergenceWarning: lb
fgs failed to converge (status=1):
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Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\alpika.gupta\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:444: ConvergenceWarning: lb
fgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\alpika.gupta\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:444: ConvergenceWarning: lb
fgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\alpika.gupta\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:444: ConvergenceWarning: lb
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Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
0.7668831168831169
```

```
C:\Users\alpika.gupta\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:444: ConvergenceWarning: lb
fgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
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fgs failed to converge (status=1):
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Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Note: In this lesson, we saw the use of the ensemble learning methods, and in the next lesson, we will be working on Recommender Systems.