
LightGBM

Release 2.3.1

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LightGBM is a gradient boosting framework that uses tree based learning algorithms. It is designed to be distributed and efficient with the following advantages:

- Faster training speed and higher efficiency.
- Lower memory usage.
- Better accuracy.
- Support of parallel and GPU learning.
- Capable of handling large-scale data.

For more details, please refer to [Features](#).

CHAPTER 1

Installation Guide

Here is the guide for the build of LightGBM CLI version.

All instructions below are aimed to compile 64-bit version of LightGBM. It is worth to compile 32-bit version only in very rare special cases of environmental limitations. 32-bit version is slow and untested, so use it on your own risk and don't forget to adjust some commands in this guide.

For the build of Python-package and R-package, please refer to [Python-package](#) and [R-package](#) folders respectively.

Also you can download artifacts of the latest successful build in master branch: .

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- *Windows*
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1.1 Windows

On Windows LightGBM can be built using

- **Visual Studio;**

- **CMake** and **VS Build Tools**;
- **CMake** and **MinGW**.

1.1.1 Visual Studio (or VS Build Tools)

With GUI

1. Install [Visual Studio](#) (2015 or newer).
2. Download [zip archive](#) and unzip it.
3. Go to LightGBM-master/windows folder.
4. Open LightGBM.sln file with **Visual Studio**, choose Release configuration and click BUILD -> Build Solution (Ctrl+Shift+B).

If you have errors about **Platform Toolset**, go to PROJECT -> Properties -> Configuration Properties -> General and select the toolset installed on your machine.

The .exe file will be in LightGBM-master/windows/x64/Release folder.

From Command Line

1. Install [Git for Windows](#), [CMake](#) (3.8 or higher) and [VS Build Tools](#) (**VS Build Tools** is not needed if **Visual Studio** (2015 or newer) is already installed).
2. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM
cd LightGBM
mkdir build
cd build
cmake -A x64 ..
cmake --build . --target ALL_BUILD --config Release
```

The .exe and .dll files will be in LightGBM/Release folder.

1.1.2 MinGW-w64

1. Install [Git for Windows](#), [CMake](#) and [MinGW-w64](#).
2. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM
cd LightGBM
mkdir build
cd build
cmake -G "MinGW Makefiles" ..
mingw32-make.exe -j4
```

The .exe and .dll files will be in LightGBM/ folder.

Note: You may need to run the `cmake -G "MinGW Makefiles" ..` one more time if you encounter the `sh.exe was found in your PATH error`.

It is recommended to use **Visual Studio** for its better multithreading efficiency in **Windows** for many-core systems (see [Question 4](#) and [Question 8](#)).

Also, you may want to read [gcc Tips](#).

1.2 Linux

On Linux LightGBM can be built using **CMake** and **gcc** or **Clang**.

1. Install **CMake**.
2. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
mkdir build ; cd build
cmake ..
make -j4
```

Note: glibc >= 2.14 is required.

Also, you may want to read [gcc Tips](#).

1.3 macOS

On macOS LightGBM can be installed using **Homebrew**, or can be built using **CMake** and **Apple Clang** or **gcc**.

1.3.1 Apple Clang

Only **Apple Clang** version 8.1 or higher is supported.

Install Using Homebrew

```
brew install lightgbm
```

Build from GitHub

1. Install **CMake** (3.12 or higher):

```
brew install cmake
```

2. Install **OpenMP**:

```
brew install libomp
```

3. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
mkdir build ; cd build

# For Mojave (10.14)
cmake \
  -DOpenMP_C_FLAGS="-Xpreprocessor -fopenmp -I$(brew --prefix libomp)/include" \
  -DOpenMP_C_LIB_NAMES="omp" \
```

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```
-DOpenMP_CXX_FLAGS="-Xpreprocessor -fopenmp -I$(brew --prefix libomp)/include" \
-DOpenMP_CXX_LIB_NAMES="omp" \
-DOpenMP_omp_LIBRARY=$(brew --prefix libomp)/lib/libomp.dylib \
..

# For High Sierra or earlier (<= 10.13)
cmake ..

make -j4
```

1.3.2 gcc

1. Install **CMake** (3.2 or higher):

```
brew install cmake
```

2. Install **gcc**:

```
brew install gcc
```

3. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
export CXX=g++-7 CC=gcc-7 # replace "7" with version of gcc installed on your
↪machine
mkdir build ; cd build
cmake ..
make -j4
```

Also, you may want to read [gcc Tips](#).

1.4 Docker

Refer to [Docker](#) folder.

1.5 Build Threadless Version (not Recommended)

The default build version of LightGBM is based on OpenMP. However, you can build the LightGBM without OpenMP support, but it is **strongly not recommended**.

1.5.1 Windows

On Windows version of LightGBM without OpenMP support can be built using

- **Visual Studio**;
- **CMake** and **VS Build Tools**;
- **CMake** and **MinGW**.

Visual Studio (or VS Build Tools)

With GUI

1. Install [Visual Studio](#) (2015 or newer).
2. Download [zip archive](#) and unzip it.
3. Go to LightGBM-master/windows folder.
4. Open LightGBM.sln file with **Visual Studio**.
5. Go to PROJECT -> Properties -> Configuration Properties -> C/C++ -> Language and change the OpenMP Support property to No (/openmp-).
6. Get back to the project's main screen, then choose Release configuration and click BUILD -> Build Solution (Ctrl+Shift+B).

If you have errors about **Platform Toolset**, go to PROJECT -> Properties -> Configuration Properties -> General and select the toolset installed on your machine.

The .exe file will be in LightGBM-master/windows/x64/Release folder.

From Command Line

1. Install [Git for Windows](#), [CMake](#) (3.8 or higher) and [VS Build Tools](#) (**VS Build Tools** is not needed if **Visual Studio** (2015 or newer) is already installed).
2. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM
cd LightGBM
mkdir build
cd build
cmake -A x64 -DUSE_OPENMP=OFF ..
cmake --build . --target ALL_BUILD --config Release
```

The .exe and .dll files will be in LightGBM/Release folder.

MinGW-w64

1. Install [Git for Windows](#), [CMake](#) and [MinGW-w64](#).
2. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM
cd LightGBM
mkdir build
cd build
cmake -G "MinGW Makefiles" -DUSE_OPENMP=OFF ..
mingw32-make.exe -j4
```

The .exe and .dll files will be in LightGBM/ folder.

Note: You may need to run the `cmake -G "MinGW Makefiles" -DUSE_OPENMP=OFF ..` one more time if you encounter the `sh.exe was found in your PATH error`.

1.5.2 Linux

On Linux version of LightGBM without OpenMP support can be built using **CMake** and **gcc** or **Clang**.

1. Install **CMake**.
2. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
mkdir build ; cd build
cmake -DUSE_OPENMP=OFF ..
make -j4
```

Note: glibc >= 2.14 is required.

1.5.3 macOS

On macOS version of LightGBM without OpenMP support can be built using **CMake** and **Apple Clang** or **gcc**.

Apple Clang

Only **Apple Clang** version 8.1 or higher is supported.

1. Install **CMake** (3.12 or higher):

```
brew install cmake
```

2. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
mkdir build ; cd build
cmake -DUSE_OPENMP=OFF ..
make -j4
```

gcc

1. Install **CMake** (3.2 or higher):

```
brew install cmake
```

2. Install **gcc**:

```
brew install gcc
```

3. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
export CXX=g++-7 CC=gcc-7 # replace "7" with version of gcc installed on your
↪machine
mkdir build ; cd build
cmake -DUSE_OPENMP=OFF ..
make -j4
```

1.6 Build MPI Version

The default build version of LightGBM is based on socket. LightGBM also supports MPI. MPI is a high performance communication approach with RDMA support.

If you need to run a parallel learning application with high performance communication, you can build the LightGBM with MPI support.

1.6.1 Windows

On Windows MPI version of LightGBM can be built using

- **MS MPI** and **Visual Studio**;
- **MS MPI**, **CMake** and **VS Build Tools**.

With GUI

1. You need to install **MS MPI** first. Both `msmpisdk.msi` and `msmpisetup.exe` are needed.
2. Install **Visual Studio** (2015 or newer).
3. Download [zip archive](#) and unzip it.
4. Go to `LightGBM-master/windows` folder.
5. Open `LightGBM.sln` file with **Visual Studio**, choose `Release_mpi` configuration and click BUILD -> Build Solution (`Ctrl+Shift+B`).

If you have errors about **Platform Toolset**, go to `PROJECT -> Properties -> Configuration Properties -> General` and select the toolset installed on your machine.

The `.exe` file will be in `LightGBM-master/windows/x64/Release_mpi` folder.

From Command Line

1. You need to install **MS MPI** first. Both `msmpisdk.msi` and `msmpisetup.exe` are needed.
2. Install **Git for Windows**, **CMake** (3.8 or higher) and **VS Build Tools** (**VS Build Tools** is not needed if **Visual Studio** (2015 or newer) is already installed).
3. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM
cd LightGBM
mkdir build
cd build
cmake -A x64 -DUSE_MPI=ON ..
cmake --build . --target ALL_BUILD --config Release
```

The `.exe` and `.dll` files will be in `LightGBM/Release` folder.

Note: Building MPI version by **MinGW** is not supported due to the miss of MPI library in it.

1.6.2 Linux

On Linux MPI version of LightGBM can be built using **Open MPI**, **CMake** and **gcc** or **Clang**.

1. Install **Open MPI**.
2. Install **CMake**.
3. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
mkdir build ; cd build
cmake -DUSE_MPI=ON ..
make -j4
```

Note: glibc >= 2.14 is required.

1.6.3 macOS

On macOS MPI version of LightGBM can be built using **Open MPI**, **CMake** and **Apple Clang** or **gcc**.

Apple Clang

Only **Apple Clang** version 8.1 or higher is supported.

1. Install **CMake** (3.12 or higher):

```
brew install cmake
```

2. Install **OpenMP**:

```
brew install libomp
```

3. Install **Open MPI**:

```
brew install open-mpi
```

4. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
mkdir build ; cd build

# For Mojave (10.14)
cmake \
  -DUSE_MPI=ON \
  -DOpenMP_C_FLAGS="-Xpreprocessor -fopenmp -I$(brew --prefix libomp)/include" \
  -DOpenMP_C_LIB_NAMES="omp" \
  -DOpenMP_CXX_FLAGS="-Xpreprocessor -fopenmp -I$(brew --prefix libomp)/include" \
  -DOpenMP_CXX_LIB_NAMES="omp" \
  -DOpenMP_omp_LIBRARY=$(brew --prefix libomp)/lib/libomp.dylib \
  ..

# For High Sierra or earlier (<= 10.13)
cmake -DUSE_MPI=ON ..

make -j4
```

gcc

1. Install **CMake** (3.2 or higher):

```
brew install cmake
```

2. Install **gcc**:

```
brew install gcc
```

3. Install **Open MPI**:

```
brew install open-mpi
```

4. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
export CXX=g++-7 CC=gcc-7 # replace "7" with version of gcc installed on your
↪machine
mkdir build ; cd build
cmake -DUSE_MPI=ON ..
make -j4
```

1.7 Build GPU Version

1.7.1 Linux

On Linux GPU version of LightGBM can be built using **OpenCL**, **Boost**, **CMake** and **gcc** or **Clang**.

The following dependencies should be installed before compilation:

- **OpenCL** 1.2 headers and libraries, which is usually provided by GPU manufacture.

The generic OpenCL ICD packages (for example, Debian package `ocl-icd-libopencl1` and `ocl-icd-opencl-dev`) can also be used.

- **libboost** 1.56 or later (1.61 or later is recommended).

We use Boost.Compute as the interface to GPU, which is part of the Boost library since version 1.61. However, since we include the source code of Boost.Compute as a submodule, we only require the host has Boost 1.56 or later installed. We also use Boost.Align for memory allocation. Boost.Compute requires Boost.System and Boost.Filesystem to store offline kernel cache.

The following Debian packages should provide necessary Boost libraries: `libboost-dev`, `libboost-system-dev`, `libboost-filesystem-dev`.

- **CMake** 3.2 or later.

To build LightGBM GPU version, run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
mkdir build ; cd build
cmake -DUSE_GPU=1 ..
# if you have installed NVIDIA CUDA to a customized location, you should specify
↪paths to OpenCL headers and library like the following:
# cmake -DUSE_GPU=1 -DOpenCL_LIBRARY=/usr/local/cuda/lib64/libOpenCL.so -DOpenCL_
↪INCLUDE_DIR=/usr/local/cuda/include/ ..
make -j4
```

1.7.2 Windows

On Windows GPU version of LightGBM can be built using **OpenCL**, **Boost**, **CMake** and **VS Build Tools** or **MinGW**. If you use **MinGW**, the build procedure is similar to the build on Linux. Refer to [GPU Windows Compilation](#) to get more details.

Following procedure is for the **MSVC** (Microsoft Visual C++) build.

1. Install [Git for Windows](#), [CMake](#) (3.8 or higher) and [VS Build Tools](#) (**VS Build Tools** is not needed if **Visual Studio** (2015 or newer) is installed).
2. Install **OpenCL** for Windows. The installation depends on the brand (NVIDIA, AMD, Intel) of your GPU card.
 - For running on Intel, get [Intel SDK for OpenCL](#).
 - For running on AMD, get AMD APP SDK.
 - For running on NVIDIA, get [CUDA Toolkit](#).

Further reading and correspondence table: [GPU SDK Correspondence and Device Targeting Table](#).

3. Install [Boost Binaries](#).

Note: Match your Visual C++ version:

Visual Studio 2015 -> msvc-14.0-64.exe,

Visual Studio 2017 -> msvc-14.1-64.exe,

Visual Studio 2019 -> msvc-14.2-64.exe.

4. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM
cd LightGBM
mkdir build
cd build
cmake -A x64 -DUSE_GPU=1 -DBOOST_ROOT=C:/local/boost_1_63_0 -DBOOST_LIBRARYDIR=C:/
↪local/boost_1_63_0/lib64-msvc-14.0 ..
# if you have installed NVIDIA CUDA to a customized location, you should specify ↪
↪paths to OpenCL headers and library like the following:
# cmake -A x64 -DUSE_GPU=1 -DBOOST_ROOT=C:/local/boost_1_63_0 -DBOOST_
↪LIBRARYDIR=C:/local/boost_1_63_0/lib64-msvc-14.0 -DOpenCL_LIBRARY="C:/Program ↪
↪Files/NVIDIA GPU Computing Toolkit/CUDA/v10.0/lib/x64/OpenCL.lib" -DOpenCL_
↪INCLUDE_DIR="C:/Program Files/NVIDIA GPU Computing Toolkit/CUDA/v10.0/include" .
↪.
cmake --build . --target ALL_BUILD --config Release
```

Note: C:/local/boost_1_63_0 and C:/local/boost_1_63_0/lib64-msvc-14.0 are locations of your **Boost** binaries (assuming you've downloaded 1.63.0 version for Visual Studio 2015).

1.7.3 Docker

Refer to [GPU Docker](#) folder.

1.8 Build HDFS Version

HDFS version of LightGBM was tested on CDH-5.14.4 cluster.

1.8.1 Linux

On Linux HDFS version of LightGBM can be built using **CMake** and **gcc**.

1. Install **CMake**.
2. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
mkdir build ; cd build
cmake -DUSE_HDFS=ON ..
# if you have installed HDFS to a customized location, you should specify paths
# to HDFS headers (hdfs.h) and library (libhdfs.so) like the following:
# cmake \
#   -DUSE_HDFS=ON \
#   -DHDFS_LIB="/opt/cloudera/parcels/CDH-5.14.4-1.cdh5.14.4.p0.3/lib64/libhdfs.so" \
#   -DHDFS_INCLUDE_DIR="/opt/cloudera/parcels/CDH-5.14.4-1.cdh5.14.4.p0.3/include/" \
#   ..
make -j4
```

1.9 Build Java Wrapper

By the following instructions you can generate a JAR file containing the LightGBM **C API** wrapped by **SWIG**.

1.9.1 Windows

On Windows Java wrapper of LightGBM can be built using **Java**, **SWIG**, **CMake** and **VS Build Tools** or **MinGW**.

VS Build Tools

1. Install **Git for Windows**, **CMake** (3.8 or higher) and **VS Build Tools** (**VS Build Tools** is not needed if **Visual Studio** (2015 or newer) is already installed).
2. Install **SWIG** and **Java** (also make sure that `JAVA_HOME` is set properly).
3. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM
cd LightGBM
mkdir build
cd build
cmake -A x64 -DUSE_SWIG=ON ..
cmake --build . --target ALL_BUILD --config Release
```

The `.jar` file will be in `LightGBM/build` folder and the `.dll` files will be in `LightGBM/Release` folder.

MinGW-w64

1. Install **Git for Windows**, **CMake** and **MinGW-w64**.
2. Install **SWIG** and **Java** (also make sure that `JAVA_HOME` is set properly).

3. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM
cd LightGBM
mkdir build
cd build
cmake -G "MinGW Makefiles" -DUSE_SWIG=ON ..
mingw32-make.exe -j4
```

The `.jar` file will be in `LightGBM/build` folder and the `.dll` files will be in `LightGBM/` folder.

Note: You may need to run the `cmake -G "MinGW Makefiles" -DUSE_SWIG=ON ..` one more time if you encounter the `sh.exe was found in your PATH error`.

It is recommended to use **VS Build Tools (Visual Studio)** for its better multithreading efficiency in **Windows** for many-core systems (see [Question 4](#) and [Question 8](#)).

Also, you may want to read [gcc Tips](#).

1.9.2 Linux

On Linux Java wrapper of LightGBM can be built using **Java**, **SWIG**, **CMake** and **gcc** or **Clang**.

1. Install **CMake**, **SWIG** and **Java** (also make sure that `JAVA_HOME` is set properly).
2. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
mkdir build ; cd build
cmake -DUSE_SWIG=ON ..
make -j4
```

1.9.3 macOS

On macOS Java wrapper of LightGBM can be built using **Java**, **SWIG**, **CMake** and **Apple Clang** or **gcc**.

First, install **SWIG** and **Java** (also make sure that `JAVA_HOME` is set properly). Then, either follow the **Apple Clang** or **gcc** installation instructions below.

Apple Clang

Only **Apple Clang** version 8.1 or higher is supported.

1. Install **CMake** (3.12 or higher):

```
brew install cmake
```

2. Install **OpenMP**:

```
brew install libomp
```

3. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
mkdir build ; cd build

# For Mojave (10.14)
cmake \
  -DUSE_SWIG=ON \
  -DAPPLE_OUTPUT_DYLIB=ON \
  -DOpenMP_C_FLAGS="-Xpreprocessor -fopenmp -I$(brew --prefix libomp)/include" \
  -DOpenMP_C_LIB_NAMES="omp" \
  -DOpenMP_CXX_FLAGS="-Xpreprocessor -fopenmp -I$(brew --prefix libomp)/include" \
  -DOpenMP_CXX_LIB_NAMES="omp" \
  -DOpenMP_omp_LIBRARY=$(brew --prefix libomp)/lib/libomp.dylib \
  ..

# For High Sierra or earlier (<= 10.13)
cmake -DUSE_SWIG=ON -DAPPLE_OUTPUT_DYLIB=ON ..

make -j4
```

gcc

1. Install CMake (3.2 or higher):

```
brew install cmake
```

2. Install gcc:

```
brew install gcc
```

3. Run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM ; cd LightGBM
export CXX=g++-7 CC=gcc-7 # replace "7" with version of gcc installed on your
↪machine
mkdir build ; cd build
cmake -DUSE_SWIG=ON -DAPPLE_OUTPUT_DYLIB=ON ..
make -j4
```

Also, you may want to read [gcc Tips](#).

This is a quick start guide for LightGBM CLI version.

Follow the [Installation Guide](#) to install LightGBM first.

List of other helpful links

- [Parameters](#)
- [Parameters Tuning](#)
- [Python-package Quick Start](#)
- [Python API](#)

2.1 Training Data Format

LightGBM supports input data files with [CSV](#), [TSV](#) and [LibSVM](#) (zero-based) formats.

Files could be both with and without [headers](#).

[Label column](#) could be specified both by index and by name.

Some columns could be [ignored](#).

2.1.1 Categorical Feature Support

LightGBM can use categorical features directly (without one-hot encoding). The experiment on [Expo data](#) shows about 8x speed-up compared with one-hot encoding.

For the setting details, please refer to the `categorical_feature` [parameter](#).

2.1.2 Weight and Query/Group Data

LightGBM also supports weighted training, it needs an additional [weight data](#). And it needs an additional [query data](#) for ranking task.

Also, [weight](#) and [query](#) data could be specified as columns in training data in the same manner as label.

2.2 Parameters Quick Look

The parameters format is `key1=value1 key2=value2`

Parameters can be set both in config file and command line. If one parameter appears in both command line and config file, LightGBM will use the parameter from the command line.

The most important parameters which new users should take a look to are located into [Core Parameters](#) and the top of [Learning Control Parameters](#) sections of the full detailed list of [LightGBM's parameters](#).

2.3 Run LightGBM

```
"./lightgbm" config=your_config_file other_args ...
```

Parameters can be set both in the config file and command line, and the parameters in command line have higher priority than in the config file. For example, the following command line will keep `num_trees=10` and ignore the same parameter in the config file.

```
"./lightgbm" config=train.conf num_trees=10
```

2.4 Examples

- [Binary Classification](#)
- [Regression](#)
- [Lambdarank](#)
- [Parallel Learning](#)

Python-package Introduction

This document gives a basic walkthrough of LightGBM Python-package.

List of other helpful links

- [Python Examples](#)
- [Python API](#)
- [Parameters Tuning](#)

3.1 Install

Install Python-package dependencies, `setuptools`, `wheel`, `numpy` and `scipy` are required, `scikit-learn` is required for `sklearn` interface and recommended:

```
pip install setuptools wheel numpy scipy scikit-learn -U
```

Refer to [Python-package](#) folder for the installation guide.

To verify your installation, try to `import lightgbm` in Python:

```
import lightgbm as lgb
```

3.2 Data Interface

The LightGBM Python module can load data from:

- LibSVM (zero-based) / TSV / CSV / TXT format file
- NumPy 2D array(s), pandas DataFrame, H2O DataTable's Frame, SciPy sparse matrix
- LightGBM binary file

The data is stored in a `Dataset` object.

Many of the examples in this page use functionality from `numpy`. To run the examples, be sure to import `numpy` in your session.

```
import numpy as np
```

To load a LibSVM (zero-based) text file or a LightGBM binary file into Dataset:

```
train_data = lgb.Dataset('train.svm.bin')
```

To load a numpy array into Dataset:

```
data = np.random.rand(500, 10) # 500 entities, each contains 10 features
label = np.random.randint(2, size=500) # binary target
train_data = lgb.Dataset(data, label=label)
```

To load a `scipy.sparse.csr_matrix` array into Dataset:

```
import scipy
csr = scipy.sparse.csr_matrix((data, (row, col)))
train_data = lgb.Dataset(csr)
```

Saving Dataset into a LightGBM binary file will make loading faster:

```
train_data = lgb.Dataset('train.svm.txt')
train_data.save_binary('train.bin')
```

Create validation data:

```
validation_data = train_data.create_valid('validation.svm')
```

or

```
validation_data = lgb.Dataset('validation.svm', reference=train_data)
```

In LightGBM, the validation data should be aligned with training data.

Specific feature names and categorical features:

```
train_data = lgb.Dataset(data, label=label, feature_name=['c1', 'c2', 'c3'],
    ↪categorical_feature=['c3'])
```

LightGBM can use categorical features as input directly. It doesn't need to convert to one-hot coding, and is much faster than one-hot coding (about 8x speed-up).

Note: You should convert your categorical features to `int` type before you construct `Dataset`.

Weights can be set when needed:

```
w = np.random.rand(500, )
train_data = lgb.Dataset(data, label=label, weight=w)
```

or

```
train_data = lgb.Dataset(data, label=label)
w = np.random.rand(500, )
train_data.set_weight(w)
```


And you can use `Dataset.set_init_score()` to set initial score, and `Dataset.set_group()` to set group/query data for ranking tasks.

Memory efficient usage:

The `Dataset` object in LightGBM is very memory-efficient, it only needs to save discrete bins. However, Numpy/Array/Pandas object is memory expensive. If you are concerned about your memory consumption, you can save memory by:

1. Set `free_raw_data=True` (default is `True`) when constructing the `Dataset`
2. Explicitly set `raw_data=None` after the `Dataset` has been constructed
3. Call `gc`

3.3 Setting Parameters

LightGBM can use a dictionary to set [Parameters](#). For instance:

- Booster parameters:

```
param = {'num_leaves': 31, 'objective': 'binary'}
param['metric'] = 'auc'
```

- You can also specify multiple eval metrics:

```
param['metric'] = ['auc', 'binary_logloss']
```

3.4 Training

Training a model requires a parameter list and data set:

```
num_round = 10
bst = lgb.train(param, train_data, num_round, valid_sets=[validation_data])
```

After training, the model can be saved:

```
bst.save_model('model.txt')
```

The trained model can also be dumped to JSON format:

```
json_model = bst.dump_model()
```

A saved model can be loaded:

```
bst = lgb.Booster(model_file='model.txt') # init model
```

3.5 CV

Training with 5-fold CV:

```
lgb.cv(param, train_data, num_round, nfold=5)
```

3.6 Early Stopping

If you have a validation set, you can use early stopping to find the optimal number of boosting rounds. Early stopping requires at least one set in `valid_sets`. If there is more than one, it will use all of them except the training data:

```
bst = lgb.train(param, train_data, num_round, valid_sets=valid_sets, early_stopping_
↳ rounds=5)
bst.save_model('model.txt', num_iteration=bst.best_iteration)
```

The model will train until the validation score stops improving. Validation score needs to improve at least every `early_stopping_rounds` to continue training.

The index of iteration that has the best performance will be saved in the `best_iteration` field if early stopping logic is enabled by setting `early_stopping_rounds`. Note that `train()` will return a model from the best iteration.

This works with both metrics to minimize (L2, log loss, etc.) and to maximize (NDCG, AUC, etc.). Note that if you specify more than one evaluation metric, all of them will be used for early stopping. However, you can change this behavior and make LightGBM check only the first metric for early stopping by passing `first_metric_only=True` in `param` or `early_stopping` callback constructor.

3.7 Prediction

A model that has been trained or loaded can perform predictions on datasets:

```
# 7 entities, each contains 10 features
data = np.random.rand(7, 10)
ypred = bst.predict(data)
```

If early stopping is enabled during training, you can get predictions from the best iteration with `bst.best_iteration`:

```
ypred = bst.predict(data, num_iteration=bst.best_iteration)
```

This is a conceptual overview of how LightGBM works[1]. We assume familiarity with decision tree boosting algorithms to focus instead on aspects of LightGBM that may differ from other boosting packages. For detailed algorithms, please refer to the citations or source code.

4.1 Optimization in Speed and Memory Usage

Many boosting tools use pre-sort-based algorithms[2, 3] (e.g. default algorithm in xgboost) for decision tree learning. It is a simple solution, but not easy to optimize.

LightGBM uses histogram-based algorithms[4, 5, 6], which bucket continuous feature (attribute) values into discrete bins. This speeds up training and reduces memory usage. Advantages of histogram-based algorithms include the following:

- **Reduced cost of calculating the gain for each split**
 - Pre-sort-based algorithms have time complexity $O(\#data)$
 - Computing the histogram has time complexity $O(\#data)$, but this involves only a fast sum-up operation. Once the histogram is constructed, a histogram-based algorithm has time complexity $O(\#bins)$, and $\#bins$ is far smaller than $\#data$.
- **Use histogram subtraction for further speedup**
 - To get one leaf's histograms in a binary tree, use the histogram subtraction of its parent and its neighbor
 - So it needs to construct histograms for only one leaf (with smaller $\#data$ than its neighbor). It then can get histograms of its neighbor by histogram subtraction with small cost ($O(\#bins)$)
- **Reduce memory usage**
 - Replaces continuous values with discrete bins. If $\#bins$ is small, can use small data type, e.g. `uint8_t`, to store training data
 - No need to store additional information for pre-sorting feature values
- **Reduce communication cost for parallel learning**

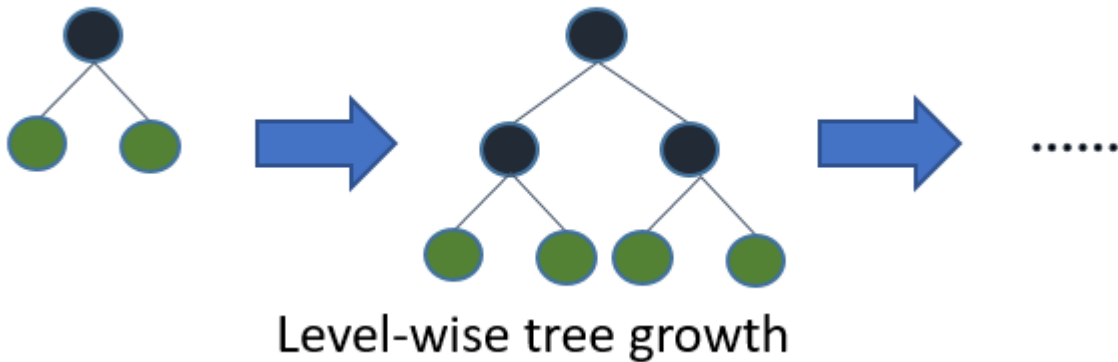
4.2 Sparse Optimization

- Need only $O(2 * \text{\#non_zero_data})$ to construct histogram for sparse features

4.3 Optimization in Accuracy

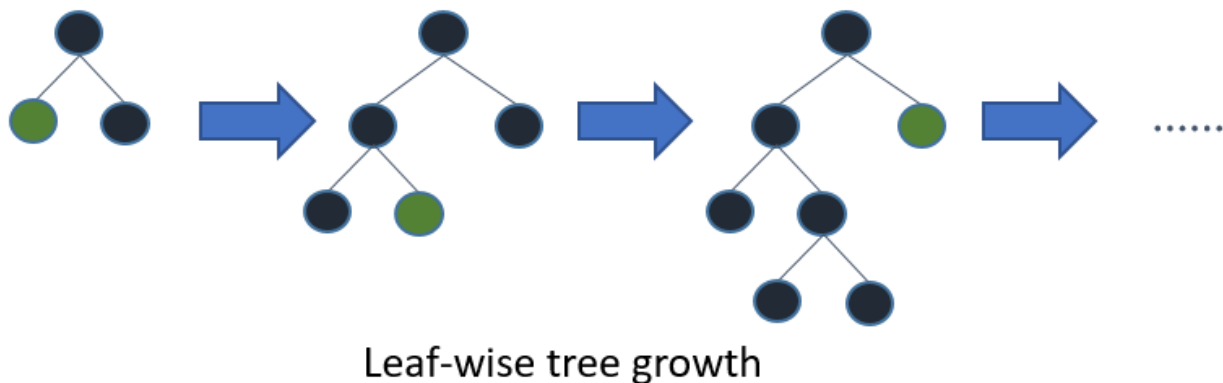
4.3.1 Leaf-wise (Best-first) Tree Growth

Most decision tree learning algorithms grow trees by level (depth)-wise, like the following image:



LightGBM grows trees leaf-wise (best-first)[7]. It will choose the leaf with max delta loss to grow. Holding `#leaf` fixed, leaf-wise algorithms tend to achieve lower loss than level-wise algorithms.

Leaf-wise may cause over-fitting when `#data` is small, so LightGBM includes the `max_depth` parameter to limit tree depth. However, trees still grow leaf-wise even when `max_depth` is specified.



4.3.2 Optimal Split for Categorical Features

It is common to represent categorical features with one-hot encoding, but this approach is suboptimal for tree learners. Particularly for high-cardinality categorical features, a tree built on one-hot features tends to be unbalanced and needs to grow very deep to achieve good accuracy.

Instead of one-hot encoding, the optimal solution is to split on a categorical feature by partitioning its categories into 2 subsets. If the feature has k categories, there are $2^{k-1} - 1$ possible partitions. But there is an efficient solution for regression trees[8]. It needs about $O(k * \log(k))$ to find the optimal partition.

The basic idea is to sort the categories according to the training objective at each split. More specifically, LightGBM sorts the histogram (for a categorical feature) according to its accumulated values (`sum_gradient / sum_hessian`) and then finds the best split on the sorted histogram.

4.4 Optimization in Network Communication

It only needs to use some collective communication algorithms, like “All reduce”, “All gather” and “Reduce scatter”, in parallel learning of LightGBM. LightGBM implements state-of-art algorithms[9]. These collective communication algorithms can provide much better performance than point-to-point communication.

4.5 Optimization in Parallel Learning

LightGBM provides the following parallel learning algorithms.

4.5.1 Feature Parallel

Traditional Algorithm

Feature parallel aims to parallelize the “Find Best Split” in the decision tree. The procedure of traditional feature parallel is:

1. Partition data vertically (different machines have different feature set).
2. Workers find local best split point {feature, threshold} on local feature set.
3. Communicate local best splits with each other and get the best one.
4. Worker with best split to perform split, then send the split result of data to other workers.
5. Other workers split data according to received data.

The shortcomings of traditional feature parallel:

- Has computation overhead, since it cannot speed up “split”, whose time complexity is $O(\#data)$. Thus, feature parallel cannot speed up well when $\#data$ is large.
- Need communication of split result, which costs about $O(\#data / 8)$ (one bit for one data).

Feature Parallel in LightGBM

Since feature parallel cannot speed up well when $\#data$ is large, we make a little change: instead of partitioning data vertically, every worker holds the full data. Thus, LightGBM doesn’t need to communicate for split result of data since every worker knows how to split data. And $\#data$ won’t be larger, so it is reasonable to hold the full data in every machine.

The procedure of feature parallel in LightGBM:

1. Workers find local best split point {feature, threshold} on local feature set.
2. Communicate local best splits with each other and get the best one.

3. Perform best split.

However, this feature parallel algorithm still suffers from computation overhead for “split” when `#data` is large. So it will be better to use data parallel when `#data` is large.

4.5.2 Data Parallel

Traditional Algorithm

Data parallel aims to parallelize the whole decision learning. The procedure of data parallel is:

1. Partition data horizontally.
2. Workers use local data to construct local histograms.
3. Merge global histograms from all local histograms.
4. Find best split from merged global histograms, then perform splits.

The shortcomings of traditional data parallel:

- High communication cost. If using point-to-point communication algorithm, communication cost for one machine is about $O(\#machine * \#feature * \#bin)$. If using collective communication algorithm (e.g. “All Reduce”), communication cost is about $O(2 * \#feature * \#bin)$ (check cost of “All Reduce” in chapter 4.5 at [9]).

Data Parallel in LightGBM

We reduce communication cost of data parallel in LightGBM:

1. Instead of “Merge global histograms from all local histograms”, LightGBM uses “Reduce Scatter” to merge histograms of different (non-overlapping) features for different workers. Then workers find the local best split on local merged histograms and sync up the global best split.
2. As aforementioned, LightGBM uses histogram subtraction to speed up training. Based on this, we can communicate histograms only for one leaf, and get its neighbor’s histograms by subtraction as well.

All things considered, data parallel in LightGBM has time complexity $O(0.5 * \#feature * \#bin)$.

4.5.3 Voting Parallel

Voting parallel further reduces the communication cost in *Data Parallel* to constant cost. It uses two-stage voting to reduce the communication cost of feature histograms[10].

4.6 GPU Support

Thanks @huanzhang12 for contributing this feature. Please read [11] to get more details.

- GPU Installation
- GPU Tutorial

4.7 Applications and Metrics

LightGBM supports the following applications:

- regression, the objective function is L2 loss
- binary classification, the objective function is logloss
- multi classification
- cross-entropy, the objective function is logloss and supports training on non-binary labels
- lambdarank, the objective function is lambdarank with NDCG

LightGBM supports the following metrics:

- L1 loss
- L2 loss
- Log loss
- Classification error rate
- AUC
- NDCG
- MAP
- Multi-class log loss
- Multi-class error rate
- Fair
- Huber
- Poisson
- Quantile
- MAPE
- Kullback-Leibler
- Gamma
- Tweedie

For more details, please refer to [Parameters](#).

4.8 Other Features

- Limit `max_depth` of tree while grows tree leaf-wise
- [DART](#)
- L1/L2 regularization
- Bagging
- Column (feature) sub-sample
- Continued train with input GBDT model
- Continued train with the input score file

- Weighted training
- Validation metric output during training
- Multiple validation data
- Multiple metrics
- Early stopping (both training and prediction)
- Prediction for leaf index

For more details, please refer to [Parameters](#).

4.9 References

- [1] Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, Tie-Yan Liu. “[LightGBM: A Highly Efficient Gradient Boosting Decision Tree](#).” Advances in Neural Information Processing Systems 30 (NIPS 2017), pp. 3149-3157.
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- [3] Shafer, John, Rakesh Agrawal, and Manish Mehta. “SPRINT: A scalable parallel classifier for data mining.” Proc. 1996 Int. Conf. Very Large Data Bases. 1996.
- [4] Ranka, Sanjay, and V. Singh. “CLOUDS: A decision tree classifier for large datasets.” Proceedings of the 4th Knowledge Discovery and Data Mining Conference. 1998.
- [5] Machado, F. P. “Communication and memory efficient parallel decision tree construction.” (2003).
- [6] Li, Ping, Qiang Wu, and Christopher J. Burges. “Mcrank: Learning to rank using multiple classification and gradient boosting.” Advances in Neural Information Processing Systems 20 (NIPS 2007).
- [7] Shi, Haijian. “Best-first decision tree learning.” Diss. The University of Waikato, 2007.
- [8] Walter D. Fisher. “[On Grouping for Maximum Homogeneity](#).” Journal of the American Statistical Association. Vol. 53, No. 284 (Dec., 1958), pp. 789-798.
- [9] Thakur, Rajeev, Rolf Rabenseifner, and William Gropp. “[Optimization of collective communication operations in MPICH](#).” International Journal of High Performance Computing Applications 19.1 (2005), pp. 49-66.
- [10] Qi Meng, Guolin Ke, Taifeng Wang, Wei Chen, Qiwei Ye, Zhi-Ming Ma, Tie-Yan Liu. “[A Communication-Efficient Parallel Algorithm for Decision Tree](#).” Advances in Neural Information Processing Systems 29 (NIPS 2016), pp. 1279-1287.
- [11] Huan Zhang, Si Si and Cho-Jui Hsieh. “[GPU Acceleration for Large-scale Tree Boosting](#).” SysML Conference, 2018.

5.1 Comparison Experiment

For the detailed experiment scripts and output logs, please refer to this [repo](#).

5.1.1 Data

We used 5 datasets to conduct our comparison experiments. Details of data are listed in the following table:

| Data | Task | Link | #Train_Set | #Feature | Comments |
|-----------|-----------------------|----------------------|------------|----------|--|
| Higgs | Binary classification | link | 10,500,000 | 28 | last 500,000 samples were used as test set |
| Yahoo LTR | Learning to rank | link | 473,134 | 700 | set1.train as train, set1.test as test |
| MS LTR | Learning to rank | link | 2,270,296 | 137 | {S1,S2,S3} as train set, {S5} as test set |
| Expo | Binary classification | link | 11,000,000 | 700 | last 1,000,000 samples were used as test set |
| Allstate | Binary classification | link | 13,184,290 | 4228 | last 1,000,000 samples were used as test set |

5.1.2 Environment

We ran all experiments on a single Linux server with the following specifications:

| OS | CPU | Memory |
|------------------|----------------|---------------------|
| Ubuntu 14.04 LTS | 2 * E5-2670 v3 | DDR4 2133Mhz, 256GB |

5.1.3 Baseline

We used `xgboost` as a baseline.

Both `xgboost` and `LightGBM` were built with OpenMP support.

5.1.4 Settings

We set up total 3 settings for experiments. The parameters of these settings are:

1. `xgboost`:

```
eta = 0.1
max_depth = 8
num_round = 500
nthread = 16
tree_method = exact
min_child_weight = 100
```

2. `xgboost_hist` (using histogram based algorithm):

```
eta = 0.1
num_round = 500
nthread = 16
tree_method = approx
min_child_weight = 100
tree_method = hist
grow_policy = lossguide
max_depth = 0
max_leaves = 255
```

3. `LightGBM`:

```
learning_rate = 0.1
num_leaves = 255
num_trees = 500
num_threads = 16
min_data_in_leaf = 0
min_sum_hessian_in_leaf = 100
```

`xgboost` grows trees depth-wise and controls model complexity by `max_depth`. `LightGBM` uses a leaf-wise algorithm instead and controls model complexity by `num_leaves`. So we cannot compare them in the exact same model setting. For the tradeoff, we use `xgboost` with `max_depth=8`, which will have max number leaves to 255, to compare with `LightGBM` with `num_leaves=255`.

Other parameters are default values.

5.1.5 Result

Speed

We compared speed using only the training task without any test or metric output. We didn't count the time for IO.

The following table is the comparison of time cost:

| Data | xgboost | xgboost_hist | LightGBM |
|-----------|-----------|--------------|---------------------|
| Higgs | 3794.34 s | 551.898 s | 238.505513 s |
| Yahoo LTR | 674.322 s | 265.302 s | 150.18644 s |
| MS LTR | 1251.27 s | 385.201 s | 215.320316 s |
| Expo | 1607.35 s | 588.253 s | 138.504179 s |
| Allstate | 2867.22 s | 1355.71 s | 348.084475 s |

LightGBM ran faster than xgboost on all experiment data sets.

Accuracy

We computed all accuracy metrics only on the test data set.

| Data | Metric | xgboost | xgboost_hist | LightGBM |
|-----------|--------------------|----------|-----------------|-----------------|
| Higgs | AUC | 0.839593 | 0.845605 | 0.845154 |
| Yahoo LTR | NDCG ₁ | 0.719748 | 0.720223 | 0.732466 |
| | NDCG ₃ | 0.717813 | 0.721519 | 0.738048 |
| | NDCG ₅ | 0.737849 | 0.739904 | 0.756548 |
| | NDCG ₁₀ | 0.78089 | 0.783013 | 0.796818 |
| MS LTR | NDCG ₁ | 0.483956 | 0.488649 | 0.524255 |
| | NDCG ₃ | 0.467951 | 0.473184 | 0.505327 |
| | NDCG ₅ | 0.472476 | 0.477438 | 0.510007 |
| | NDCG ₁₀ | 0.492429 | 0.496967 | 0.527371 |
| Expo | AUC | 0.756713 | 0.777777 | 0.777543 |
| Allstate | AUC | 0.607201 | 0.609042 | 0.609167 |

Memory Consumption

We monitored RES while running training task. And we set `two_round=true` (this will increase data-loading time and reduce peak memory usage but not affect training speed or accuracy) in LightGBM to reduce peak memory usage.

| Data | xgboost | xgboost_hist | LightGBM |
|-----------|---------|--------------|----------------|
| Higgs | 4.853GB | 3.784GB | 0.868GB |
| Yahoo LTR | 1.907GB | 1.468GB | 0.831GB |
| MS LTR | 5.469GB | 3.654GB | 0.886GB |
| Expo | 1.553GB | 1.393GB | 0.543GB |
| Allstate | 6.237GB | 4.990GB | 1.027GB |

5.2 Parallel Experiment

5.2.1 Data

We used a terabyte click log dataset to conduct parallel experiments. Details are listed in following table:

| Data | Task | Link | #Data | #Feature |
|--------|-----------------------|----------------------|---------------|----------|
| Criteo | Binary classification | link | 1,700,000,000 | 67 |

This data contains 13 integer features and 26 categorical features for 24 days of click logs. We statisticized the clickthrough rate (CTR) and count for these 26 categorical features from the first ten days. Then we used next ten days' data, after replacing the categorical features by the corresponding CTR and count, as training data. The processed training data have a total of 1.7 billions records and 67 features.

5.2.2 Environment

We ran our experiments on 16 Windows servers with the following specifications:

| OS | CPU | Memory | Network Adapter |
|---------------------|----------------|---------------------|---|
| Windows Server 2012 | 2 * E5-2670 v2 | DDR3 1600Mhz, 256GB | Mellanox ConnectX-3, 54Gbps, RDMA support |

5.2.3 Settings

```
learning_rate = 0.1
num_leaves = 255
num_trees = 100
num_thread = 16
tree_learner = data
```

We used data parallel here because this data is large in `#data` but small in `#feature`. Other parameters were default values.

5.2.4 Results

| #Machine | Time per Tree | Memory Usage(per Machine) |
|----------|---------------|---------------------------|
| 1 | 627.8 s | 176GB |
| 2 | 311 s | 87GB |
| 4 | 156 s | 43GB |
| 8 | 80 s | 22GB |
| 16 | 42 s | 11GB |

The results show that LightGBM achieves a linear speedup with parallel learning.

5.3 GPU Experiments

Refer to [GPU Performance](#).

This page contains descriptions of all parameters in LightGBM.

List of other helpful links

- [Python API](#)
- [Parameters Tuning](#)

External Links

- [Laurae++ Interactive Documentation](#)

6.1 Parameters Format

The parameters format is `key1=value1 key2=value2 ...`. Parameters can be set both in config file and command line. By using command line, parameters should not have spaces before and after `=`. By using config files, one line can only contain one parameter. You can use `#` to comment.

If one parameter appears in both command line and config file, LightGBM will use the parameter from the command line.

6.2 Core Parameters

- `config`, `default = ""`, `type = string`, `aliases: config_file`
 - path of config file
 - **Note:** can be used only in CLI version
- `task`, `default = train`, `type = enum`, `options: train, predict, convert_model, refit`, `aliases: task_type`
 - `train`, for training, `aliases: training`

- predict, for prediction, aliases: prediction, test
- convert_model, for converting model file into if-else format, see more information in *IO Parameters*
- refit, for refitting existing models with new data, aliases: refit_tree
- **Note:** can be used only in CLI version; for language-specific packages you can use the correspondent functions
- objective , default = regression, type = enum, options: regression, regression_l1, huber, fair, poisson, quantile, mape, gamma, tweedie, binary, multiclass, multiclassova, cross_entropy, cross_entropy_lambda, lambdarank, aliases: objective_type, app, application
 - regression application
 - * regression, L2 loss, aliases: regression_l2, l2, mean_squared_error, mse, l2_root, root_mean_squared_error, rmse
 - * regression_l1, L1 loss, aliases: l1, mean_absolute_error, mae
 - * huber, **Huber loss**
 - * fair, **Fair loss**
 - * poisson, **Poisson regression**
 - * quantile, **Quantile regression**
 - * mape, **MAPE loss**, aliases: mean_absolute_percentage_error
 - * gamma, Gamma regression with log-link. It might be useful, e.g., for modeling insurance claims severity, or for any target that might be **gamma-distributed**
 - * tweedie, Tweedie regression with log-link. It might be useful, e.g., for modeling total loss in insurance, or for any target that might be **tweedie-distributed**
 - binary, binary **log loss** classification (or logistic regression). Requires labels in {0, 1}; see cross-entropy application for general probability labels in [0, 1]
 - multi-class classification application
 - * multiclass, **softmax** objective function, aliases: softmax
 - * multiclassova, **One-vs-All** binary objective function, aliases: multiclass_ova, ova, ovr
 - * num_class should be set as well
 - cross-entropy application
 - * cross_entropy, objective function for cross-entropy (with optional linear weights), aliases: xentropy
 - * cross_entropy_lambda, alternative parameterization of cross-entropy, aliases: xentlambda
 - * label is anything in interval [0, 1]
 - lambdarank, **lambdarank** application
 - * label should be int type in lambdarank tasks, and larger number represents the higher relevance (e.g. 0:bad, 1:fair, 2:good, 3:perfect)
 - * **label_gain** can be used to set the gain (weight) of int label
 - * all values in label must be smaller than number of elements in label_gain
- boosting , default = gbd, type = enum, options: gbd, rf, dart, goss, aliases: boosting_type, boost

- gbdt, traditional Gradient Boosting Decision Tree, aliases: gbrt
- rf, Random Forest, aliases: random_forest
- dart, [Dropouts meet Multiple Additive Regression Trees](#)
- goss, Gradient-based One-Side Sampling
- data , default = "", type = string, aliases: train, train_data, train_data_file, data_filename
 - path of training data, LightGBM will train from this data
 - **Note:** can be used only in CLI version
- valid , default = "", type = string, aliases: test, valid_data, valid_data_file, test_data, test_data_file, valid_filenames
 - path(s) of validation/test data, LightGBM will output metrics for these data
 - support multiple validation data, separated by ,
 - **Note:** can be used only in CLI version
- num_iterations , default = 100, type = int, aliases: num_iteration, n_iter, num_tree, num_trees, num_round, num_rounds, num_boost_round, n_estimators, constraints: num_iterations >= 0
 - number of boosting iterations
 - **Note:** internally, LightGBM constructs num_class * num_iterations trees for multi-class classification problems
- learning_rate , default = 0.1, type = double, aliases: shrinkage_rate, eta, constraints: learning_rate > 0.0
 - shrinkage rate
 - in dart, it also affects on normalization weights of dropped trees
- num_leaves , default = 31, type = int, aliases: num_leaf, max_leaves, max_leaf, constraints: 1 < num_leaves <= 131072
 - max number of leaves in one tree
- tree_learner , default = serial, type = enum, options: serial, feature, data, voting, aliases: tree, tree_type, tree_learner_type
 - serial, single machine tree learner
 - feature, feature parallel tree learner, aliases: feature_parallel
 - data, data parallel tree learner, aliases: data_parallel
 - voting, voting parallel tree learner, aliases: voting_parallel
 - refer to [Parallel Learning Guide](#) to get more details
- num_threads , default = 0, type = int, aliases: num_thread, nthread, nthreads, n_jobs
 - number of threads for LightGBM
 - 0 means default number of threads in OpenMP
 - for the best speed, set this to the number of **real CPU cores**, not the number of threads (most CPUs use [hyper-threading](#) to generate 2 threads per CPU core)
 - do not set it too large if your dataset is small (for instance, do not use 64 threads for a dataset with 10,000 rows)

- be aware a task manager or any similar CPU monitoring tool might report that cores not being fully utilized.
This is normal
- for parallel learning, do not use all CPU cores because this will cause poor performance for the network communication
- `device_type` , default = `cpu`, type = `enum`, options: `cpu`, `gpu`, aliases: `device`
 - device for the tree learning, you can use GPU to achieve the faster learning
 - **Note:** it is recommended to use the smaller `max_bin` (e.g. 63) to get the better speed up
 - **Note:** for the faster speed, GPU uses 32-bit float point to sum up by default, so this may affect the accuracy for some tasks. You can set `gpu_use_dp=true` to enable 64-bit float point, but it will slow down the training
 - **Note:** refer to [Installation Guide](#) to build LightGBM with GPU support
- `seed` , default = `None`, type = `int`, aliases: `random_seed`, `random_state`
 - this seed is used to generate other seeds, e.g. `data_random_seed`, `feature_fraction_seed`, etc.
 - by default, this seed is unused in favor of default values of other seeds
 - this seed has lower priority in comparison with other seeds, which means that it will be overridden, if you set other seeds explicitly

6.3 Learning Control Parameters

- `max_depth` , default = `-1`, type = `int`
 - limit the max depth for tree model. This is used to deal with over-fitting when `#data` is small. Tree still grows leaf-wise
 - `<= 0` means no limit
- `min_data_in_leaf` , default = `20`, type = `int`, aliases: `min_data_per_leaf`, `min_data`, `min_child_samples`, constraints: `min_data_in_leaf >= 0`
 - minimal number of data in one leaf. Can be used to deal with over-fitting
- `min_sum_hessian_in_leaf` , default = `1e-3`, type = `double`, aliases: `min_sum_hessian_per_leaf`, `min_sum_hessian`, `min_hessian`, `min_child_weight`, constraints: `min_sum_hessian_in_leaf >= 0.0`
 - minimal sum hessian in one leaf. Like `min_data_in_leaf`, it can be used to deal with over-fitting
- `bagging_fraction` , default = `1.0`, type = `double`, aliases: `sub_row`, `subsample`, `bagging`, constraints: `0.0 < bagging_fraction <= 1.0`
 - like `feature_fraction`, but this will randomly select part of data without resampling
 - can be used to speed up training
 - can be used to deal with over-fitting
 - **Note:** to enable bagging, `bagging_freq` should be set to a non zero value as well
- `pos_bagging_fraction` , default = `1.0`, type = `double`, aliases: `pos_sub_row`, `pos_subsample`, `pos_bagging`, constraints: `0.0 < pos_bagging_fraction <= 1.0`
 - used only in binary application

- used for imbalanced binary classification problem, will randomly sample `#pos_samples * pos_bagging_fraction` positive samples in bagging
- should be used together with `neg_bagging_fraction`
- set this to 1.0 to disable
- **Note:** to enable this, you need to set `bagging_freq` and `neg_bagging_fraction` as well
- **Note:** if both `pos_bagging_fraction` and `neg_bagging_fraction` are set to 1.0, balanced bagging is disabled
- **Note:** if balanced bagging is enabled, `bagging_fraction` will be ignored
- `neg_bagging_fraction`, default = 1.0, type = double, aliases: `neg_sub_row`, `neg_subsample`, `neg_bagging`, constraints: `0.0 < neg_bagging_fraction <= 1.0`
 - used only in binary application
 - used for imbalanced binary classification problem, will randomly sample `#neg_samples * neg_bagging_fraction` negative samples in bagging
 - should be used together with `pos_bagging_fraction`
 - set this to 1.0 to disable
 - **Note:** to enable this, you need to set `bagging_freq` and `pos_bagging_fraction` as well
 - **Note:** if both `pos_bagging_fraction` and `neg_bagging_fraction` are set to 1.0, balanced bagging is disabled
 - **Note:** if balanced bagging is enabled, `bagging_fraction` will be ignored
- `bagging_freq`, default = 0, type = int, aliases: `subsample_freq`
 - frequency for bagging
 - 0 means disable bagging; k means perform bagging at every k iteration
 - **Note:** to enable bagging, `bagging_fraction` should be set to value smaller than 1.0 as well
- `bagging_seed`, default = 3, type = int, aliases: `bagging_fraction_seed`
 - random seed for bagging
- `feature_fraction`, default = 1.0, type = double, aliases: `sub_feature`, `colsample_bytree`, constraints: `0.0 < feature_fraction <= 1.0`
 - LightGBM will randomly select part of features on each iteration (tree) if `feature_fraction` smaller than 1.0. For example, if you set it to 0.8, LightGBM will select 80% of features before training each tree
 - can be used to speed up training
 - can be used to deal with over-fitting
- `feature_fraction_bynode`, default = 1.0, type = double, aliases: `sub_feature_bynode`, `colsample_bynode`, constraints: `0.0 < feature_fraction_bynode <= 1.0`
 - LightGBM will randomly select part of features on each tree node if `feature_fraction_bynode` smaller than 1.0. For example, if you set it to 0.8, LightGBM will select 80% of features at each tree node
 - can be used to deal with over-fitting
 - **Note:** unlike `feature_fraction`, this cannot speed up training

- **Note:** if both `feature_fraction` and `feature_fraction_bynode` are smaller than 1.0, the final fraction of each node is `feature_fraction * feature_fraction_bynode`
- `feature_fraction_seed`, default = 2, type = int
 - random seed for `feature_fraction`
- `early_stopping_round`, default = 0, type = int, aliases: `early_stopping_rounds`, `early_stopping`, `n_iter_no_change`
 - will stop training if one metric of one validation data doesn't improve in last `early_stopping_round` rounds
 - `<= 0` means disable
- `first_metric_only`, default = false, type = bool
 - set this to `true`, if you want to use only the first metric for early stopping
- `max_delta_step`, default = 0.0, type = double, aliases: `max_tree_output`, `max_leaf_output`
 - used to limit the max output of tree leaves
 - `<= 0` means no constraint
 - the final max output of leaves is `learning_rate * max_delta_step`
- `lambda_l1`, default = 0.0, type = double, aliases: `reg_alpha`, constraints: `lambda_l1 >= 0.0`
 - L1 regularization
- `lambda_l2`, default = 0.0, type = double, aliases: `reg_lambda`, `lambda`, constraints: `lambda_l2 >= 0.0`
 - L2 regularization
- `min_gain_to_split`, default = 0.0, type = double, aliases: `min_split_gain`, constraints: `min_gain_to_split >= 0.0`
 - the minimal gain to perform split
- `drop_rate`, default = 0.1, type = double, aliases: `rate_drop`, constraints: `0.0 <= drop_rate <= 1.0`
 - used only in dart
 - dropout rate: a fraction of previous trees to drop during the dropout
- `max_drop`, default = 50, type = int
 - used only in dart
 - max number of dropped trees during one boosting iteration
 - `<= 0` means no limit
- `skip_drop`, default = 0.5, type = double, constraints: `0.0 <= skip_drop <= 1.0`
 - used only in dart
 - probability of skipping the dropout procedure during a boosting iteration
- `xgboost_dart_mode`, default = false, type = bool
 - used only in dart
 - set this to `true`, if you want to use xgboost dart mode
- `uniform_drop`, default = false, type = bool

- used only in `dart`
 - set this to `true`, if you want to use uniform drop
- `drop_seed`, default = 4, type = int
 - used only in `dart`
 - random seed to choose dropping models
- `top_rate`, default = 0.2, type = double, constraints: $0.0 \leq \text{top_rate} \leq 1.0$
 - used only in `goss`
 - the retain ratio of large gradient data
- `other_rate`, default = 0.1, type = double, constraints: $0.0 \leq \text{other_rate} \leq 1.0$
 - used only in `goss`
 - the retain ratio of small gradient data
- `min_data_per_group`, default = 100, type = int, constraints: $\text{min_data_per_group} > 0$
 - minimal number of data per categorical group
- `max_cat_threshold`, default = 32, type = int, constraints: $\text{max_cat_threshold} > 0$
 - used for the categorical features
 - limit the max threshold points in categorical features
- `cat_l2`, default = 10.0, type = double, constraints: $\text{cat_l2} \geq 0.0$
 - used for the categorical features
 - L2 regularization in categorical split
- `cat_smooth`, default = 10.0, type = double, constraints: $\text{cat_smooth} \geq 0.0$
 - used for the categorical features
 - this can reduce the effect of noises in categorical features, especially for categories with few data
- `max_cat_to_onehot`, default = 4, type = int, constraints: $\text{max_cat_to_onehot} > 0$
 - when number of categories of one feature smaller than or equal to `max_cat_to_onehot`, one-vs-other split algorithm will be used
- `top_k`, default = 20, type = int, aliases: `topk`, constraints: $\text{top_k} > 0$
 - used in [Voting parallel](#)
 - set this to larger value for more accurate result, but it will slow down the training speed
- `monotone_constraints`, default = None, type = multi-int, aliases: `mc`, `monotone_constraint`
 - used for constraints of monotonic features
 - 1 means increasing, -1 means decreasing, 0 means non-constraint
 - you need to specify all features in order. For example, `mc=-1, 0, 1` means decreasing for 1st feature, non-constraint for 2nd feature and increasing for the 3rd feature
- `feature_contri`, default = None, type = multi-double, aliases: `feature_contrib`, `fc`, `fp`, `feature_penalty`
 - used to control feature's split gain, will use $\text{gain}[i] = \max(0, \text{feature_contri}[i]) * \text{gain}[i]$ to replace the split gain of i-th feature

- you need to specify all features in order
- `forced_splits_filename` , `default = ""` , `type = string` , `aliases: fs, forced_splits_filename, forced_splits_file, forced_splits`
 - path to a `.json` file that specifies splits to force at the top of every decision tree before best-first learning commences
 - `.json` file can be arbitrarily nested, and each split contains `feature` , `threshold` fields, as well as `left` and `right` fields representing subsplits
 - categorical splits are forced in a one-hot fashion, with `left` representing the split containing the feature value and `right` representing other values
 - **Note:** the forced split logic will be ignored, if the split makes gain worse
 - see [this file](#) as an example
- `forced_bins_filename` , `default = ""` , `type = string`
 - path to a `.json` file that specifies bin upper bounds for some or all features
 - `.json` file should contain an array of objects, each containing the word `feature` (integer feature index) and `bin_upper_bound` (array of thresholds for binning)
 - see [this file](#) as an example
- `refit_decay_rate` , `default = 0.9` , `type = double` , `constraints: 0.0 <= refit_decay_rate <= 1.0`
 - decay rate of refit task, will use `leaf_output = refit_decay_rate * old_leaf_output + (1.0 - refit_decay_rate) * new_leaf_output` to refit trees
 - used only in refit task in CLI version or as argument in `refit` function in language-specific package
- `cegb_tradeoff` , `default = 1.0` , `type = double` , `constraints: cegb_tradeoff >= 0.0`
 - cost-effective gradient boosting multiplier for all penalties
- `cegb_penalty_split` , `default = 0.0` , `type = double` , `constraints: cegb_penalty_split >= 0.0`
 - cost-effective gradient-boosting penalty for splitting a node
- `cegb_penalty_feature_lazy` , `default = 0, 0, ..., 0` , `type = multi-double`
 - cost-effective gradient boosting penalty for using a feature
 - applied per data point
- `cegb_penalty_feature_coupled` , `default = 0, 0, ..., 0` , `type = multi-double`
 - cost-effective gradient boosting penalty for using a feature
 - applied once per forest

6.4 IO Parameters

- `verbosity` , `default = 1` , `type = int` , `aliases: verbose`
 - controls the level of LightGBM's verbosity
 - `< 0`: Fatal, `= 0`: Error (Warning), `= 1`: Info, `> 1`: Debug
- `max_bin` , `default = 255` , `type = int` , `constraints: max_bin > 1`
 - max number of bins that feature values will be bucketed in

- small number of bins may reduce training accuracy but may increase general power (deal with over-fitting)
- LightGBM will auto compress memory according to `max_bin`. For example, LightGBM will use `uint8_t` for feature value if `max_bin=255`
- `max_bin_by_feature`, default = None, type = multi-int
 - max number of bins for each feature
 - if not specified, will use `max_bin` for all features
- `min_data_in_bin`, default = 3, type = int, constraints: `min_data_in_bin > 0`
 - minimal number of data inside one bin
 - use this to avoid one-data-one-bin (potential over-fitting)
- `bin_construct_sample_cnt`, default = 200000, type = int, aliases: `subsample_for_bin`, constraints: `bin_construct_sample_cnt > 0`
 - number of data that sampled to construct histogram bins
 - setting this to larger value will give better training result, but will increase data loading time
 - set this to larger value if data is very sparse
- `histogram_pool_size`, default = -1.0, type = double, aliases: `hist_pool_size`
 - max cache size in MB for historical histogram
 - < 0 means no limit
- `data_random_seed`, default = 1, type = int, aliases: `data_seed`
 - random seed for data partition in parallel learning (excluding the `feature_parallel` mode)
- `output_model`, default = `LightGBM_model.txt`, type = string, aliases: `model_output`, `model_out`
 - filename of output model in training
 - **Note:** can be used only in CLI version
- `snapshot_freq`, default = -1, type = int, aliases: `save_period`
 - frequency of saving model file snapshot
 - set this to positive value to enable this function. For example, the model file will be snapshotted at each iteration if `snapshot_freq=1`
 - **Note:** can be used only in CLI version
- `input_model`, default = "", type = string, aliases: `model_input`, `model_in`
 - filename of input model
 - for prediction task, this model will be applied to prediction data
 - for train task, training will be continued from this model
 - **Note:** can be used only in CLI version
- `output_result`, default = `LightGBM_predict_result.txt`, type = string, aliases: `predict_result`, `prediction_result`, `predict_name`, `prediction_name`, `pred_name`, `name_pred`
 - filename of prediction result in prediction task
 - **Note:** can be used only in CLI version

- `initscore_filename` , `default = ""`, `type = string`, `aliases:` `init_score_filename`, `init_score_file`, `init_score`, `input_init_score`
 - path of file with training initial scores
 - if "", will use `train_data_file + .init` (if exists)
 - **Note:** works only in case of loading data directly from file
- `valid_data_initscores` , `default = ""`, `type = string`, `aliases:` `valid_data_init_scores`, `valid_init_score_file`, `valid_init_score`
 - path(s) of file(s) with validation initial scores
 - if "", will use `valid_data_file + .init` (if exists)
 - separate by , for multi-validation data
 - **Note:** works only in case of loading data directly from file
- `pre_partition` , `default = false`, `type = bool`, `aliases:` `is_pre_partition`
 - used for parallel learning (excluding the `feature_parallel` mode)
 - true if training data are pre-partitioned, and different machines use different partitions
- `enable_bundle` , `default = true`, `type = bool`, `aliases:` `is_enable_bundle`, `bundle`
 - set this to `false` to disable Exclusive Feature Bundling (EFB), which is described in [LightGBM: A Highly Efficient Gradient Boosting Decision Tree](#)
 - **Note:** disabling this may cause the slow training speed for sparse datasets
- `max_conflict_rate` , `default = 0.0`, `type = double`, `constraints:` `0.0 <= max_conflict_rate < 1.0`
 - max conflict rate for bundles in EFB
 - set this to `0.0` to disallow the conflict and provide more accurate results
 - set this to a larger value to achieve faster speed
- `is_enable_sparse` , `default = true`, `type = bool`, `aliases:` `is_sparse`, `enable_sparse`, `sparse`
 - used to enable/disable sparse optimization
- `sparse_threshold` , `default = 0.8`, `type = double`, `constraints:` `0.0 < sparse_threshold <= 1.0`
 - the threshold of zero elements percentage for treating a feature as a sparse one
- `use_missing` , `default = true`, `type = bool`
 - set this to `false` to disable the special handle of missing value
- `zero_as_missing` , `default = false`, `type = bool`
 - set this to `true` to treat all zero as missing values (including the unshown values in LibSVM / sparse matrices)
 - set this to `false` to use `na` for representing missing values
- `two_round` , `default = false`, `type = bool`, `aliases:` `two_round_loading`, `use_two_round_loading`
 - set this to `true` if data file is too big to fit in memory
 - by default, LightGBM will map data file to memory and load features from memory. This will provide faster data loading speed, but may cause run out of memory error when the data file is very big

- **Note:** works only in case of loading data directly from file
- `save_binary` , default = `false`, type = `bool`, aliases: `is_save_binary`, `is_save_binary_file`
 - if `true`, LightGBM will save the dataset (including validation data) to a binary file. This speeds up the data loading for the next time
 - **Note:** can be used only in CLI version; for language-specific packages you can use the correspondent function
- `header` , default = `false`, type = `bool`, aliases: `has_header`
 - set this to `true` if input data has header
 - **Note:** works only in case of loading data directly from file
- `label_column` , default = `" "`, type = `int` or `string`, aliases: `label`
 - used to specify the label column
 - use number for index, e.g. `label=0` means `column_0` is the label
 - add a prefix `name :` for column name, e.g. `label=name:is_click`
 - **Note:** works only in case of loading data directly from file
- `weight_column` , default = `" "`, type = `int` or `string`, aliases: `weight`
 - used to specify the weight column
 - use number for index, e.g. `weight=0` means `column_0` is the weight
 - add a prefix `name :` for column name, e.g. `weight=name:weight`
 - **Note:** works only in case of loading data directly from file
 - **Note:** index starts from 0 and it doesn't count the label column when passing type is `int`, e.g. when label is `column_0`, and weight is `column_1`, the correct parameter is `weight=0`
- `group_column` , default = `" "`, type = `int` or `string`, aliases: `group`, `group_id`, `query_column`, `query`, `query_id`
 - used to specify the query/group id column
 - use number for index, e.g. `query=0` means `column_0` is the query id
 - add a prefix `name :` for column name, e.g. `query=name:query_id`
 - **Note:** works only in case of loading data directly from file
 - **Note:** data should be grouped by `query_id`
 - **Note:** index starts from 0 and it doesn't count the label column when passing type is `int`, e.g. when label is `column_0` and `query_id` is `column_1`, the correct parameter is `query=0`
- `ignore_column` , default = `" "`, type = `multi-int` or `string`, aliases: `ignore_feature`, `blacklist`
 - used to specify some ignoring columns in training
 - use number for index, e.g. `ignore_column=0, 1, 2` means `column_0`, `column_1` and `column_2` will be ignored
 - add a prefix `name :` for column name, e.g. `ignore_column=name:c1, c2, c3` means `c1`, `c2` and `c3` will be ignored
 - **Note:** works only in case of loading data directly from file
 - **Note:** index starts from 0 and it doesn't count the label column when passing type is `int`

- **Note:** despite the fact that specified columns will be completely ignored during the training, they still should have a valid format allowing LightGBM to load file successfully
- `categorical_feature` , `default = ""`, `type = multi-int or string`, aliases: `cat_feature`, `categorical_column`, `cat_column`
 - used to specify categorical features
 - use number for index, e.g. `categorical_feature=0,1,2` means `column_0`, `column_1` and `column_2` are categorical features
 - add a prefix name: for column name, e.g. `categorical_feature=name:c1,c2,c3` means `c1`, `c2` and `c3` are categorical features
 - **Note:** only supports categorical with `int` type
 - **Note:** index starts from 0 and it doesn't count the label column when passing type is `int`
 - **Note:** all values should be less than `Int32.MaxValue (2147483647)`
 - **Note:** using large values could be memory consuming. Tree decision rule works best when categorical features are presented by consecutive integers starting from zero
 - **Note:** all negative values will be treated as **missing values**
 - **Note:** the output cannot be monotonically constrained with respect to a categorical feature
- `predict_raw_score` , `default = false`, `type = bool`, aliases: `is_predict_raw_score`, `predict_rawscore`, `raw_score`
 - used only in prediction task
 - set this to `true` to predict only the raw scores
 - set this to `false` to predict transformed scores
- `predict_leaf_index` , `default = false`, `type = bool`, aliases: `is_predict_leaf_index`, `leaf_index`
 - used only in prediction task
 - set this to `true` to predict with leaf index of all trees
- `predict_contrib` , `default = false`, `type = bool`, aliases: `is_predict_contrib`, `contrib`
 - used only in prediction task
 - set this to `true` to estimate **SHAP values**, which represent how each feature contributes to each prediction
 - produces `#features + 1` values where the last value is the expected value of the model output over the training data
 - **Note:** if you want to get more explanation for your model's predictions using SHAP values like SHAP interaction values, you can install [shap package](#)
 - **Note:** unlike the shap package, with `predict_contrib` we return a matrix with an extra column, where the last column is the expected value
- `num_iteration_predict` , `default = -1`, `type = int`
 - used only in prediction task
 - used to specify how many trained iterations will be used in prediction
 - `<= 0` means no limit
- `pred_early_stop` , `default = false`, `type = bool`

- used only in prediction task
- if `true`, will use early-stopping to speed up the prediction. May affect the accuracy
- `pred_early_stop_freq`, default = 10, type = int
 - used only in prediction task
 - the frequency of checking early-stopping prediction
- `pred_early_stop_margin`, default = 10.0, type = double
 - used only in prediction task
 - the threshold of margin in early-stopping prediction
- `convert_model_language`, default = "", type = string
 - used only in `convert_model` task
 - only `cpp` is supported yet
 - if `convert_model_language` is set and `task=train`, the model will be also converted
 - **Note:** can be used only in CLI version
- `convert_model`, default = `gbdt_prediction.cpp`, type = string, aliases: `convert_model_file`
 - used only in `convert_model` task
 - output filename of converted model
 - **Note:** can be used only in CLI version

6.5 Objective Parameters

- `num_class`, default = 1, type = int, aliases: `num_classes`, constraints: `num_class > 0`
 - used only in multi-class classification application
- `is_unbalance`, default = false, type = bool, aliases: `unbalance`, `unbalanced_sets`
 - used only in binary and multiclassova applications
 - set this to `true` if training data are unbalanced
 - **Note:** while enabling this should increase the overall performance metric of your model, it will also result in poor estimates of the individual class probabilities
 - **Note:** this parameter cannot be used at the same time with `scale_pos_weight`, choose only **one** of them
- `scale_pos_weight`, default = 1.0, type = double, constraints: `scale_pos_weight > 0.0`
 - used only in binary and multiclassova applications
 - weight of labels with positive class
 - **Note:** while enabling this should increase the overall performance metric of your model, it will also result in poor estimates of the individual class probabilities
 - **Note:** this parameter cannot be used at the same time with `is_unbalance`, choose only **one** of them
- `sigmoid`, default = 1.0, type = double, constraints: `sigmoid > 0.0`
 - used only in binary and multiclassova classification and in lambdarank applications

- parameter for the sigmoid function
- `boost_from_average` , `default = true`, `type = bool`
 - used only in regression, binary, multiclassova and cross-entropy applications
 - adjusts initial score to the mean of labels for faster convergence
- `reg_sqrt` , `default = false`, `type = bool`
 - used only in regression application
 - used to fit `sqrt(label)` instead of original values and prediction result will be also automatically converted to `prediction^2`
 - might be useful in case of large-range labels
- `alpha` , `default = 0.9`, `type = double`, constraints: `alpha > 0.0`
 - used only in huber and quantile regression applications
 - parameter for [Huber loss](#) and [Quantile regression](#)
- `fair_c` , `default = 1.0`, `type = double`, constraints: `fair_c > 0.0`
 - used only in fair regression application
 - parameter for [Fair loss](#)
- `poisson_max_delta_step` , `default = 0.7`, `type = double`, constraints: `poisson_max_delta_step > 0.0`
 - used only in poisson regression application
 - parameter for [Poisson regression](#) to safeguard optimization
- `tweedie_variance_power` , `default = 1.5`, `type = double`, constraints: `1.0 <= tweedie_variance_power < 2.0`
 - used only in tweedie regression application
 - used to control the variance of the tweedie distribution
 - set this closer to 2 to shift towards a **Gamma** distribution
 - set this closer to 1 to shift towards a **Poisson** distribution
- `max_position` , `default = 20`, `type = int`, constraints: `max_position > 0`
 - used only in lambdarank application
 - optimizes [NDCG](#) at this position
- `lamdamart_norm` , `default = true`, `type = bool`
 - used only in lambdarank application
 - set this to `true` to normalize the lambdas for different queries, and improve the performance for unbalanced data
 - set this to `false` to enforce the original lamdamart algorithm
- `label_gain` , `default = 0, 1, 3, 7, 15, 31, 63, ..., 2^30-1`, `type = multi-double`
 - used only in lambdarank application
 - relevant gain for labels. For example, the gain of label 2 is 3 in case of default label gains
 - separate by ,

6.6 Metric Parameters

- `metric`, default = "", type = multi-enum, aliases: `metrics`, `metric_types`
 - metric(s) to be evaluated on the evaluation set(s)
 - * "" (empty string or not specified) means that metric corresponding to specified objective will be used (this is possible only for pre-defined objective functions, otherwise no evaluation metric will be added)
 - * "None" (string, **not** a None value) means that no metric will be registered, aliases: `na`, `null`, `custom`
 - * `l1`, absolute loss, aliases: `mean_absolute_error`, `mae`, `regression_l1`
 - * `l2`, square loss, aliases: `mean_squared_error`, `mse`, `regression_l2`, `regression`
 - * `rmse`, root square loss, aliases: `root_mean_squared_error`, `l2_root`
 - * `quantile`, [Quantile regression](#)
 - * `mape`, [MAPE loss](#), aliases: `mean_absolute_percentage_error`
 - * `huber`, [Huber loss](#)
 - * `fair`, [Fair loss](#)
 - * `poisson`, negative log-likelihood for [Poisson regression](#)
 - * `gamma`, negative log-likelihood for **Gamma** regression
 - * `gamma_deviance`, residual deviance for **Gamma** regression
 - * `tweedie`, negative log-likelihood for **Tweedie** regression
 - * `ndcg`, [NDCG](#), aliases: `lambdarank`
 - * `map`, [MAP](#), aliases: `mean_average_precision`
 - * `auc`, [AUC](#)
 - * `binary_logloss`, [log loss](#), aliases: `binary`
 - * `binary_error`, for one sample: 0 for correct classification, 1 for error classification
 - * `multi_logloss`, log loss for multi-class classification, aliases: `multiclass`, `softmax`, `multiclassova`, `multiclass_ova`, `ova`, `ovr`
 - * `multi_error`, error rate for multi-class classification
 - * `cross_entropy`, cross-entropy (with optional linear weights), aliases: `xentropy`
 - * `cross_entropy_lambda`, “intensity-weighted” cross-entropy, aliases: `xentlambda`
 - * `kullback_leibler`, [Kullback-Leibler divergence](#), aliases: `kldiv`
 - support multiple metrics, separated by ,
- `metric_freq`, default = 1, type = int, aliases: `output_freq`, constraints: `metric_freq > 0`
 - frequency for metric output
- `is_provide_training_metric`, default = false, type = bool, aliases: `training_metric`, `is_training_metric`, `train_metric`
 - set this to true to output metric result over training dataset
 - **Note:** can be used only in CLI version

- `eval_at` , default = 1, 2, 3, 4, 5, type = multi-int, aliases: `ndcg_eval_at`, `ndcg_at`, `map_eval_at`, `map_at`
 - used only with `ndcg` and `map` metrics
 - **NDCG** and **MAP** evaluation positions, separated by ,
- `multi_error_top_k` , default = 1, type = int, constraints: `multi_error_top_k` > 0
 - used only with `multi_error` metric
 - threshold for top-k multi-error metric
 - the error on each sample is 0 if the true class is among the top `multi_error_top_k` predictions, and 1 otherwise
 - * more precisely, the error on a sample is 0 if there are at least `num_classes - multi_error_top_k` predictions strictly less than the prediction on the true class
 - when `multi_error_top_k=1` this is equivalent to the usual multi-error metric

6.7 Network Parameters

- `num_machines` , default = 1, type = int, aliases: `num_machine`, constraints: `num_machines` > 0
 - the number of machines for parallel learning application
 - this parameter is needed to be set in both **socket** and **mpi** versions
- `local_listen_port` , default = 12400, type = int, aliases: `local_port`, `port`, constraints: `local_listen_port` > 0
 - TCP listen port for local machines
 - **Note:** don't forget to allow this port in firewall settings before training
- `time_out` , default = 120, type = int, constraints: `time_out` > 0
 - socket time-out in minutes
- `machine_list_filename` , default = "", type = string, aliases: `machine_list_file`, `machine_list`, `mlist`
 - path of file that lists machines for this parallel learning application
 - each line contains one IP and one port for one machine. The format is `ip port` (space as a separator)
- `machines` , default = "", type = string, aliases: `workers`, `nodes`
 - list of machines in the following format: `ip1:port1,ip2:port2`

6.8 GPU Parameters

- `gpu_platform_id` , default = -1, type = int
 - OpenCL platform ID. Usually each GPU vendor exposes one OpenCL platform
 - -1 means the system-wide default platform
 - **Note:** refer to **GPU Targets** for more details
- `gpu_device_id` , default = -1, type = int

- OpenCL device ID in the specified platform. Each GPU in the selected platform has a unique device ID
- -1 means the default device in the selected platform
- **Note:** refer to [GPU Targets](#) for more details
- `gpu_use_dp` , `default = false`, `type = bool`
 - set this to `true` to use double precision math on GPU (by default single precision is used)

6.9 Others

6.9.1 Continued Training with Input Score

LightGBM supports continued training with initial scores. It uses an additional file to store these initial scores, like the following:

```
0.5
-0.1
0.9
...
```

It means the initial score of the first data row is 0.5, second is -0.1, and so on. The initial score file corresponds with data file line by line, and has per score per line.

And if the name of data file is `train.txt`, the initial score file should be named as `train.txt.init` and in the same folder as the data file. In this case, LightGBM will auto load initial score file if it exists.

Otherwise, you should specify the path to the custom named file with initial scores by the `initscore_filename` parameter.

6.9.2 Weight Data

LightGBM supports weighted training. It uses an additional file to store weight data, like the following:

```
1.0
0.5
0.8
...
```

It means the weight of the first data row is 1.0, second is 0.5, and so on. The weight file corresponds with data file line by line, and has per weight per line.

And if the name of data file is `train.txt`, the weight file should be named as `train.txt.weight` and placed in the same folder as the data file. In this case, LightGBM will load the weight file automatically if it exists.

Also, you can include weight column in your data file. Please refer to the `weight_column` parameter in above.

6.9.3 Query Data

For LambdaRank learning, it needs query information for training data. LightGBM uses an additional file to store query data, like the following:

```
27
18
67
...
```

It means first 27 lines samples belong to one query and next 18 lines belong to another, and so on.

Note: data should be ordered by the query.

If the name of data file is `train.txt`, the query file should be named as `train.txt.query` and placed in the same folder as the data file. In this case, LightGBM will load the query file automatically if it exists.

Also, you can include query/group id column in your data file. Please refer to the `group_column` *parameter* in above.

Parameters Tuning

This page contains parameters tuning guides for different scenarios.

List of other helpful links

- [Parameters](#)
- [Python API](#)

7.1 Tune Parameters for the Leaf-wise (Best-first) Tree

LightGBM uses the [leaf-wise](#) tree growth algorithm, while many other popular tools use depth-wise tree growth. Compared with depth-wise growth, the leaf-wise algorithm can converge much faster. However, the leaf-wise growth may be over-fitting if not used with the appropriate parameters.

To get good results using a leaf-wise tree, these are some important parameters:

1. `num_leaves`. This is the main parameter to control the complexity of the tree model. Theoretically, we can set `num_leaves = 2^(max_depth)` to obtain the same number of leaves as depth-wise tree. However, this simple conversion is not good in practice. The reason is that a leaf-wise tree is typically much deeper than a depth-wise tree for a fixed number of leaves. Unconstrained depth can induce over-fitting. Thus, when trying to tune the `num_leaves`, we should let it be smaller than `2^(max_depth)`. For example, when the `max_depth=7` the depth-wise tree can get good accuracy, but setting `num_leaves` to 127 may cause over-fitting, and setting it to 70 or 80 may get better accuracy than depth-wise.
2. `min_data_in_leaf`. This is a very important parameter to prevent over-fitting in a leaf-wise tree. Its optimal value depends on the number of training samples and `num_leaves`. Setting it to a large value can avoid growing too deep a tree, but may cause under-fitting. In practice, setting it to hundreds or thousands is enough for a large dataset.
3. `max_depth`. You also can use `max_depth` to limit the tree depth explicitly.

7.2 For Faster Speed

- Use bagging by setting `bagging_fraction` and `bagging_freq`
- Use feature sub-sampling by setting `feature_fraction`
- Use small `max_bin`
- Use `save_binary` to speed up data loading in future learning
- Use parallel learning, refer to [Parallel Learning Guide](#)

7.3 For Better Accuracy

- Use large `max_bin` (may be slower)
- Use small `learning_rate` with large `num_iterations`
- Use large `num_leaves` (may cause over-fitting)
- Use bigger training data
- Try `dart`

7.4 Deal with Over-fitting

- Use small `max_bin`
- Use small `num_leaves`
- Use `min_data_in_leaf` and `min_sum_hessian_in_leaf`
- Use bagging by set `bagging_fraction` and `bagging_freq`
- Use feature sub-sampling by set `feature_fraction`
- Use bigger training data
- Try `lambda_l1`, `lambda_l2` and `min_gain_to_split` for regularization
- Try `max_depth` to avoid growing deep tree

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Note To avoid type conversion on large data, the most of our exposed interface supports both float32 and float64, except the following:

1. gradient and Hessian;
2. current score for training and validation data.

The reason is that they are called frequently, and the type conversion on them may be time-cost.

Defines

C_API_DTYPE_FLOAT32 (0)
float32 (single precision float).

C_API_DTYPE_FLOAT64 (1)
float64 (double precision float).

C_API_DTYPE_INT32 (2)
int32.

C_API_DTYPE_INT64 (3)
int64.

C_API_DTYPE_INT8 (4)
int8.

C_API_PREDICT_CONTRIB (3)
Predict feature contributions (SHAP values).

C_API_PREDICT_LEAF_INDEX (2)
Predict leaf index.

C_API_PREDICT_NORMAL (0)
Normal prediction, with transform (if needed).

C_API_PREDICT_RAW_SCORE (1)

Predict raw score.

THREAD_LOCAL thread_local

Thread local specifier.

Typedefs

typedef void* **BoosterHandle**

Handle of booster.

typedef void* **DatasetHandle**

Handle of dataset.

Functions

static char* **LastErrorMsg** ()

Handle of error message.

Return Error message

LIGHTGBM_C_EXPORT int **LGBM_BoosterAddValidData** (*BoosterHandle* handle, const *DatasetHandle* valid_data)

Add new validation data to booster.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- valid_data: Validation dataset

LIGHTGBM_C_EXPORT int **LGBM_BoosterCalcNumPredict** (*BoosterHandle* handle, int num_row, int predict_type, int num_iteration, int64_t * out_len)

Get number of predictions.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- num_row: Number of rows
- predict_type: What should be predicted
 - C_API_PREDICT_NORMAL: normal prediction, with transform (if needed);
 - C_API_PREDICT_RAW_SCORE: raw score;
 - C_API_PREDICT_LEAF_INDEX: leaf index;
 - C_API_PREDICT_CONTRIB: feature contributions (SHAP values)
- num_iteration: Number of iterations for prediction, <= 0 means no limit
- [out] out_len: Length of prediction

LIGHTGBM_C_EXPORT int **LGBM_BoosterCreate** (const *DatasetHandle* train_data, const char * parameters, *BoosterHandle* * out)

Create a new boosting learner.

Return 0 when succeed, -1 when failure happens

Parameters

- train_data: Training dataset
- parameters: Parameters in format 'key1=value1 key2=value2'
- [out] out: Handle of created booster

LIGHTGBM_C_EXPORT int **LGBM_BoosterCreateFromModelfile** (const char * filename, int * out_num_iterations, *BoosterHandle* * out)

Load an existing booster from model file.

Return 0 when succeed, -1 when failure happens

Parameters

- filename: Filename of model
- [out] out_num_iterations: Number of iterations of this booster
- [out] out: Handle of created booster

LIGHTGBM_C_EXPORT int **LGBM_BoosterDumpModel** (*BoosterHandle* handle, int start_iteration, int num_iteration, int64_t buffer_len, int64_t * out_len, char * out_str)

Dump model to JSON.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- start_iteration: Start index of the iteration that should be dumped
- num_iteration: Index of the iteration that should be dumped, <= 0 means dump all
- buffer_len: String buffer length, if buffer_len < out_len, you should re-allocate buffer
- [out] out_len: Actual output length
- [out] out_str: JSON format string of model, should pre-allocate memory

LIGHTGBM_C_EXPORT int **LGBM_BoosterFeatureImportance** (*BoosterHandle* handle, int num_iteration, int importance_type, double * out_results)

Get model feature importance.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- num_iteration: Number of iterations for which feature importance is calculated, <= 0 means use all

- `importance_type`: Method of importance calculation:
 - 0 for split, result contains numbers of times the feature is used in a model;
 - 1 for gain, result contains total gains of splits which use the feature
- `[out] out_results`: Result array with feature importance

`LIGHTGBM_C_EXPORT int LGBM_BoosterFree (BoosterHandle handle)`
 Free space for booster.

Return 0 when succeed, -1 when failure happens

Parameters

- `handle`: Handle of booster to be freed

`LIGHTGBM_C_EXPORT int LGBM_BoosterGetCurrentIteration (BoosterHandle handle, int * out_iteration)`

Get index of the current boosting iteration.

Return 0 when succeed, -1 when failure happens

Parameters

- `handle`: Handle of booster
- `[out] out_iteration`: Index of the current boosting iteration

`LIGHTGBM_C_EXPORT int LGBM_BoosterGetEval (BoosterHandle handle, int data_idx, int * out_len, double * out_results)`

Get evaluation for training data and validation data.

Note

1. You should call `LGBM_BoosterGetEvalNames` first to get the names of evaluation datasets.
2. You should pre-allocate memory for `out_results`, you can get its length by `LGBM_BoosterGetEvalCounts`.

Return 0 when succeed, -1 when failure happens

Parameters

- `handle`: Handle of booster
- `data_idx`: Index of data, 0: training data, 1: 1st validation data, 2: 2nd validation data and so on
- `[out] out_len`: Length of output result
- `[out] out_results`: Array with evaluation results

`LIGHTGBM_C_EXPORT int LGBM_BoosterGetEvalCounts (BoosterHandle handle, int * out_len)`
 Get number of evaluation datasets.

Return 0 when succeed, -1 when failure happens

Parameters

- `handle`: Handle of booster
- `[out] out_len`: Total number of evaluation datasets

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetEvalNames** (*BoosterHandle* handle, int * out_len, char ** out_strs)

Get names of evaluation datasets.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- [out] out_len: Total number of evaluation datasets
- [out] out_strs: Names of evaluation datasets, should pre-allocate memory

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetFeatureNames** (*BoosterHandle* handle, int * out_len, char ** out_strs)

Get names of features.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- [out] out_len: Total number of features
- [out] out_strs: Names of features, should pre-allocate memory

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetLeafValue** (*BoosterHandle* handle, int tree_idx, int leaf_idx, double * out_val)

Get leaf value.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- tree_idx: Index of tree
- leaf_idx: Index of leaf
- [out] out_val: Output result from the specified leaf

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetNumClasses** (*BoosterHandle* handle, int * out_len)

Get number of classes.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- [out] out_len: Number of classes

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetNumFeature** (*BoosterHandle* handle, int * out_len)

Get number of features.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster

- [out] out_len: Total number of features

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetNumPredict** (*BoosterHandle* handle, int data_idx, int64_t * out_len)

Get number of predictions for training data and validation data (this can be used to support customized evaluation functions).

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- data_idx: Index of data, 0: training data, 1: 1st validation data, 2: 2nd validation data and so on
- [out] out_len: Number of predictions

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetPredict** (*BoosterHandle* handle, int data_idx, int64_t * out_len, double * out_result)

Get prediction for training data and validation data.

Note You should pre-allocate memory for out_result, its length is equal to num_class * num_data.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- data_idx: Index of data, 0: training data, 1: 1st validation data, 2: 2nd validation data and so on
- [out] out_len: Length of output result
- [out] out_result: Pointer to array with predictions

LIGHTGBM_C_EXPORT int **LGBM_BoosterLoadModelFromString** (const char * model_str, int * out_num_iterations, *BoosterHandle* * out)

Load an existing booster from string.

Return 0 when succeed, -1 when failure happens

Parameters

- model_str: Model string
- [out] out_num_iterations: Number of iterations of this booster
- [out] out: Handle of created booster

LIGHTGBM_C_EXPORT int **LGBM_BoosterMerge** (*BoosterHandle* handle, *BoosterHandle* other_handle)

Merge model from other_handle into handle.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster, will merge another booster into this one
- other_handle: Other handle of booster

LIGHTGBM_C_EXPORT int **LGBM_BoosterNumberOfTotalModel** (*BoosterHandle* handle, int
* out_models)

Get number of weak sub-models.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- [out] out_models: Number of weak sub-models

LIGHTGBM_C_EXPORT int **LGBM_BoosterNumModelPerIteration** (*BoosterHandle* handle, int
* out_tree_per_iteration)

Get number of trees per iteration.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- [out] out_tree_per_iteration: Number of trees per iteration

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForCSC** (*BoosterHandle* handle, const void
* col_ptr, int col_ptr_type, const
int32_t * indices, const void * data,
int data_type, int64_t ncol_ptr,
int64_t nelem, int64_t num_row, int pre-
dict_type, int num_iteration, const char
* parameter, int64_t * out_len, double
* out_result)

Make prediction for a new dataset in CSC format.

Note You should pre-allocate memory for out_result:

- for normal and raw score, its length is equal to num_class * num_data;
- for leaf index, its length is equal to num_class * num_data * num_iteration;
- for feature contributions, its length is equal to num_class * num_data * (num_feature + 1).

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- col_ptr: Pointer to column headers
- col_ptr_type: Type of col_ptr, can be C_API_DTYPE_INT32 or C_API_DTYPE_INT64
- indices: Pointer to row indices
- data: Pointer to the data space
- data_type: Type of data pointer, can be C_API_DTYPE_FLOAT32 or C_API_DTYPE_FLOAT64
- ncol_ptr: Number of columns in the matrix + 1
- nelem: Number of nonzero elements in the matrix
- num_row: Number of rows

- `predict_type`: What should be predicted
 - `C_API_PREDICT_NORMAL`: normal prediction, with transform (if needed);
 - `C_API_PREDICT_RAW_SCORE`: raw score;
 - `C_API_PREDICT_LEAF_INDEX`: leaf index;
 - `C_API_PREDICT_CONTRIB`: feature contributions (SHAP values)
- `num_iteration`: Number of iteration for prediction, ≤ 0 means no limit
- `parameter`: Other parameters for prediction, e.g. early stopping for prediction
- `[out] out_len`: Length of output result
- `[out] out_result`: Pointer to array with predictions

```
LIGHTGBM_C_EXPORT int LGBM_BoosterPredictForCSR(BoosterHandle handle, const void * indptr, int indptr_type, const int32_t * indices, const void * data, int data_type, int64_t nindptr, int64_t nelem, int64_t num_col, int predict_type, int num_iteration, const char * parameter, int64_t * out_len, double * out_result)
```

Make prediction for a new dataset in CSR format.

Note You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Return 0 when succeed, -1 when failure happens

Parameters

- `handle`: Handle of booster
- `indptr`: Pointer to row headers
- `indptr_type`: Type of `indptr`, can be `C_API_DTYPE_INT32` or `C_API_DTYPE_INT64`
- `indices`: Pointer to column indices
- `data`: Pointer to the data space
- `data_type`: Type of data pointer, can be `C_API_DTYPE_FLOAT32` or `C_API_DTYPE_FLOAT64`
- `nindptr`: Number of rows in the matrix + 1
- `nelem`: Number of nonzero elements in the matrix
- `num_col`: Number of columns
- `predict_type`: What should be predicted
 - `C_API_PREDICT_NORMAL`: normal prediction, with transform (if needed);
 - `C_API_PREDICT_RAW_SCORE`: raw score;
 - `C_API_PREDICT_LEAF_INDEX`: leaf index;

- C_API_PREDICT_CONTRIB: feature contributions (SHAP values)
- num_iteration: Number of iterations for prediction, <= 0 means no limit
- parameter: Other parameters for prediction, e.g. early stopping for prediction
- [out] out_len: Length of output result
- [out] out_result: Pointer to array with predictions

```

LIGHTGBM_C_EXPORT int LGBM_BoosterPredictForCSRSingleRow(BoosterHandle handle,
                                                         const void * indptr, int indptr_type,
                                                         const int32_t * indices, const void
                                                         * data, int data_type,
                                                         int64_t nindptr,
                                                         int64_t nelem,
                                                         int64_t num_col,
                                                         int predict_type,
                                                         int num_iteration,
                                                         const char * parameter,
                                                         int64_t * out_len,
                                                         double * out_result)

```

Make prediction for a new dataset in CSR format. This method re-uses the internal predictor structure from previous calls and is optimized for single row invocation.

Note You should pre-allocate memory for out_result:

- for normal and raw score, its length is equal to num_class * num_data;
- for leaf index, its length is equal to num_class * num_data * num_iteration;
- for feature contributions, its length is equal to num_class * num_data * (num_feature + 1).

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- indptr: Pointer to row headers
- indptr_type: Type of indptr, can be C_API_DTYPE_INT32 or C_API_DTYPE_INT64
- indices: Pointer to column indices
- data: Pointer to the data space
- data_type: Type of data pointer, can be C_API_DTYPE_FLOAT32 or C_API_DTYPE_FLOAT64
- nindptr: Number of rows in the matrix + 1
- nelem: Number of nonzero elements in the matrix
- num_col: Number of columns
- predict_type: What should be predicted
 - C_API_PREDICT_NORMAL: normal prediction, with transform (if needed);
 - C_API_PREDICT_RAW_SCORE: raw score;
 - C_API_PREDICT_LEAF_INDEX: leaf index;

- C_API_PREDICT_CONTRIB: feature contributions (SHAP values)
- num_iteration: Number of iterations for prediction, <= 0 means no limit
- parameter: Other parameters for prediction, e.g. early stopping for prediction
- [out] out_len: Length of output result
- [out] out_result: Pointer to array with predictions

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForFile** (*BoosterHandle* handle, const char * data_filename, int data_has_header, int predict_type, int num_iteration, const char * parameter, const char * result_filename)

Make prediction for file.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- data_filename: Filename of file with data
- data_has_header: Whether file has header or not
- predict_type: What should be predicted
 - C_API_PREDICT_NORMAL: normal prediction, with transform (if needed);
 - C_API_PREDICT_RAW_SCORE: raw score;
 - C_API_PREDICT_LEAF_INDEX: leaf index;
 - C_API_PREDICT_CONTRIB: feature contributions (SHAP values)
- num_iteration: Number of iterations for prediction, <= 0 means no limit
- parameter: Other parameters for prediction, e.g. early stopping for prediction
- result_filename: Filename of result file in which predictions will be written

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForMat** (*BoosterHandle* handle, const void * data, int data_type, int32_t nrow, int32_t ncol, int is_row_major, int predict_type, int num_iteration, const char * parameter, int64_t * out_len, double * out_result)

Make prediction for a new dataset.

Note You should pre-allocate memory for out_result:

- for normal and raw score, its length is equal to num_class * num_data;
- for leaf index, its length is equal to num_class * num_data * num_iteration;
- for feature contributions, its length is equal to num_class * num_data * (num_feature + 1).

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster

- `data`: Pointer to the data space
- `data_type`: Type of data pointer, can be `C_API_DTYPE_FLOAT32` or `C_API_DTYPE_FLOAT64`
- `nrow`: Number of rows
- `ncol`: Number of columns
- `is_row_major`: 1 for row-major, 0 for column-major
- `predict_type`: What should be predicted
 - `C_API_PREDICT_NORMAL`: normal prediction, with transform (if needed);
 - `C_API_PREDICT_RAW_SCORE`: raw score;
 - `C_API_PREDICT_LEAF_INDEX`: leaf index;
 - `C_API_PREDICT_CONTRIB`: feature contributions (SHAP values)
- `num_iteration`: Number of iteration for prediction, ≤ 0 means no limit
- `parameter`: Other parameters for prediction, e.g. early stopping for prediction
- `[out] out_len`: Length of output result
- `[out] out_result`: Pointer to array with predictions

```

LIGHTGBM_C_EXPORT int LGBM_BoosterPredictForMats (BoosterHandle handle, const void
                                                    ** data, int data_type, int32_t nrow,
                                                    int32_t ncol, int predict_type,
                                                    int num_iteration, const char * pa-
                                                    rameter, int64_t * out_len, double
                                                    * out_result)

```

Make prediction for a new dataset presented in a form of array of pointers to rows.

Note You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Return 0 when succeed, -1 when failure happens

Parameters

- `handle`: Handle of booster
- `data`: Pointer to the data space
- `data_type`: Type of data pointer, can be `C_API_DTYPE_FLOAT32` or `C_API_DTYPE_FLOAT64`
- `nrow`: Number of rows
- `ncol`: Number columns
- `predict_type`: What should be predicted
 - `C_API_PREDICT_NORMAL`: normal prediction, with transform (if needed);
 - `C_API_PREDICT_RAW_SCORE`: raw score;
 - `C_API_PREDICT_LEAF_INDEX`: leaf index;

- C_API_PREDICT_CONTRIB: feature contributions (SHAP values)
- num_iteration: Number of iteration for prediction, <= 0 means no limit
- parameter: Other parameters for prediction, e.g. early stopping for prediction
- [out] out_len: Length of output result
- [out] out_result: Pointer to array with predictions

```
LIGHTGBM_C_EXPORT int LGBM_BoosterPredictForMatSingleRow(BoosterHandle handle, const void * data,
                                                         int data_type, int ncol,
                                                         int is_row_major,
                                                         int predict_type,
                                                         int num_iteration,
                                                         const char * parameter, int64_t * out_len,
                                                         double * out_result)
```

Make prediction for a new dataset. This method re-uses the internal predictor structure from previous calls and is optimized for single row invocation.

Note You should pre-allocate memory for out_result:

- for normal and raw score, its length is equal to num_class * num_data;
- for leaf index, its length is equal to num_class * num_data * num_iteration;
- for feature contributions, its length is equal to num_class * num_data * (num_feature + 1).

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- data: Pointer to the data space
- data_type: Type of data pointer, can be C_API_DTYPE_FLOAT32 or C_API_DTYPE_FLOAT64
- ncol: Number columns
- is_row_major: 1 for row-major, 0 for column-major
- predict_type: What should be predicted
 - C_API_PREDICT_NORMAL: normal prediction, with transform (if needed);
 - C_API_PREDICT_RAW_SCORE: raw score;
 - C_API_PREDICT_LEAF_INDEX: leaf index;
 - C_API_PREDICT_CONTRIB: feature contributions (SHAP values)
- num_iteration: Number of iteration for prediction, <= 0 means no limit
- parameter: Other parameters for prediction, e.g. early stopping for prediction
- [out] out_len: Length of output result
- [out] out_result: Pointer to array with predictions

LIGHTGBM_C_EXPORT int **LGBM_BoosterRefit** (*BoosterHandle* handle, const int32_t * leaf_preds,
int32_t nrow, int32_t ncol)
Refit the tree model using the new data (online learning).

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- leaf_preds: Pointer to predicted leaf indices
- nrow: Number of rows of leaf_preds
- ncol: Number of columns of leaf_preds

LIGHTGBM_C_EXPORT int **LGBM_BoosterResetParameter** (*BoosterHandle* handle, const char * pa-
rameters)
Reset config for booster.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- parameters: Parameters in format 'key1=value1 key2=value2'

LIGHTGBM_C_EXPORT int **LGBM_BoosterResetTrainingData** (*BoosterHandle* handle, const
DatasetHandle train_data)
Reset training data for booster.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- train_data: Training dataset

LIGHTGBM_C_EXPORT int **LGBM_BoosterRollbackOneIter** (*BoosterHandle* handle)
Rollback one iteration.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster

LIGHTGBM_C_EXPORT int **LGBM_BoosterSaveModel** (*BoosterHandle* handle, int start_iteration,
int num_iteration, const char * filename)
Save model into file.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- start_iteration: Start index of the iteration that should be saved
- num_iteration: Index of the iteration that should be saved, <= 0 means save all
- filename: The name of the file

LIGHTGBM_C_EXPORT int **LGBM_BoosterSaveModelToString** (*BoosterHandle* *handle*, int *start_iteration*, int *num_iteration*, int64_t *buffer_len*, int64_t ** out_len*, char ** out_str*)

Save model to string.

Return 0 when succeed, -1 when failure happens

Parameters

- *handle*: Handle of booster
- *start_iteration*: Start index of the iteration that should be saved
- *num_iteration*: Index of the iteration that should be saved, ≤ 0 means save all
- *buffer_len*: String buffer length, if *buffer_len* < *out_len*, you should re-allocate buffer
- [out] *out_len*: Actual output length
- [out] *out_str*: String of model, should pre-allocate memory

LIGHTGBM_C_EXPORT int **LGBM_BoosterSetLeafValue** (*BoosterHandle* *handle*, int *tree_idx*, int *leaf_idx*, double *val*)

Set leaf value.

Return 0 when succeed, -1 when failure happens

Parameters

- *handle*: Handle of booster
- *tree_idx*: Index of tree
- *leaf_idx*: Index of leaf
- *val*: Leaf value

LIGHTGBM_C_EXPORT int **LGBM_BoosterShuffleModels** (*BoosterHandle* *handle*, int *start_iter*, int *end_iter*)

Shuffle models.

Return 0 when succeed, -1 when failure happens

Parameters

- *handle*: Handle of booster
- *start_iter*: The first iteration that will be shuffled
- *end_iter*: The last iteration that will be shuffled

LIGHTGBM_C_EXPORT int **LGBM_BoosterUpdateOneIter** (*BoosterHandle* *handle*, int ** is_finished*)

Update the model for one iteration.

Return 0 when succeed, -1 when failure happens

Parameters

- *handle*: Handle of booster
- [out] *is_finished*: 1 means the update was successfully finished (cannot split any more), 0 indicates failure

LIGHTGBM_C_EXPORT int **LGBM_BoosterUpdateOneIterCustom** (*BoosterHandle* handle, const float * grad, const float * hess, int * is_finished)

Update the model by specifying gradient and Hessian directly (this can be used to support customized loss functions).

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of booster
- grad: The first order derivative (gradient) statistics
- hess: The second order derivative (Hessian) statistics
- [out] is_finished: 1 means the update was successfully finished (cannot split any more), 0 indicates failure

LIGHTGBM_C_EXPORT int **LGBM_DatasetAddFeaturesFrom** (*DatasetHandle* target, *DatasetHandle* source)

Add features from source to target.

Return 0 when succeed, -1 when failure happens

Parameters

- target: The handle of the dataset to add features to
- source: The handle of the dataset to take features from

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateByReference** (const *DatasetHandle* reference, int64_t num_total_row, *DatasetHandle* * out)

Allocate the space for dataset and bucket feature bins according to reference dataset.

Return 0 when succeed, -1 when failure happens

Parameters

- reference: Used to align bin mapper with other dataset
- num_total_row: Number of total rows
- [out] out: Created dataset

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromCSC** (const void * col_ptr, int col_ptr_type, const int32_t * indices, const void * data, int data_type, int64_t ncol_ptr, int64_t nelem, int64_t num_row, const char * parameters, const *DatasetHandle* reference, *DatasetHandle* * out)

Create a dataset from CSC format.

Return 0 when succeed, -1 when failure happens

Parameters

- col_ptr: Pointer to column headers
- col_ptr_type: Type of col_ptr, can be C_API_DTYPE_INT32 or C_API_DTYPE_INT64

- `indices`: Pointer to row indices
- `data`: Pointer to the data space
- `data_type`: Type of data pointer, can be `C_API_DTYPE_FLOAT32` or `C_API_DTYPE_FLOAT64`
- `ncol_ptr`: Number of columns in the matrix + 1
- `nelem`: Number of nonzero elements in the matrix
- `num_row`: Number of rows
- `parameters`: Additional parameters
- `reference`: Used to align bin mapper with other dataset, nullptr means isn't used
- `[out] out`: Created dataset

```

LIGHTGBM_C_EXPORT int LGBM_DatasetCreateFromCSR(const void * indptr, int indptr_type,
const int32_t * indices, const void
* data, int data_type, int64_t nindptr,
int64_t nelem, int64_t num_col,
const char * parameters, const
DatasetHandle reference, DatasetHandle
* out)

```

Create a dataset from CSR format.

Return 0 when succeed, -1 when failure happens

Parameters

- `indptr`: Pointer to row headers
- `indptr_type`: Type of `indptr`, can be `C_API_DTYPE_INT32` or `C_API_DTYPE_INT64`
- `indices`: Pointer to column indices
- `data`: Pointer to the data space
- `data_type`: Type of data pointer, can be `C_API_DTYPE_FLOAT32` or `C_API_DTYPE_FLOAT64`
- `nindptr`: Number of rows in the matrix + 1
- `nelem`: Number of nonzero elements in the matrix
- `num_col`: Number of columns
- `parameters`: Additional parameters
- `reference`: Used to align bin mapper with other dataset, nullptr means isn't used
- `[out] out`: Created dataset

```

LIGHTGBM_C_EXPORT int LGBM_DatasetCreateFromCSRFunc(void * get_row_funptr,
int num_rows, int64_t num_col,
const char * parameters, const
DatasetHandle reference,
DatasetHandle * out)

```

Create a dataset from CSR format through callbacks.

Return 0 when succeed, -1 when failure happens

Parameters

- `get_row_funptr`: Pointer to `std::function<void(int idx, std::vector<std::pair<int, double>>& ret)>` (called for every row and expected to clear and fill `ret`)
- `num_rows`: Number of rows
- `num_col`: Number of columns
- `parameters`: Additional parameters
- `reference`: Used to align bin mapper with other dataset, nullptr means isn't used
- `[out] out`: Created dataset

`LIGHTGBM_C_EXPORT int LGBM_DatasetCreateFromFile` (`const char * filename`, `const char * parameters`, `const DatasetHandle reference`, `DatasetHandle * out`)

Load dataset from file (like LightGBM CLI version does).

Return 0 when succeed, -1 when failure happens

Parameters

- `filename`: The name of the file
- `parameters`: Additional parameters
- `reference`: Used to align bin mapper with other dataset, nullptr means isn't used
- `[out] out`: A loaded dataset

`LIGHTGBM_C_EXPORT int LGBM_DatasetCreateFromMat` (`const void * data`, `int data_type`, `int32_t nrow`, `int32_t ncol`, `int is_row_major`, `const char * parameters`, `const DatasetHandle reference`, `DatasetHandle * out`)

Create dataset from dense matrix.

Return 0 when succeed, -1 when failure happens

Parameters

- `data`: Pointer to the data space
- `data_type`: Type of data pointer, can be `C_API_DTYPE_FLOAT32` or `C_API_DTYPE_FLOAT64`
- `nrow`: Number of rows
- `ncol`: Number of columns
- `is_row_major`: 1 for row-major, 0 for column-major
- `parameters`: Additional parameters
- `reference`: Used to align bin mapper with other dataset, nullptr means isn't used
- `[out] out`: Created dataset

```
LIGHTGBM_C_EXPORT int LGBM_DatasetCreateFromMats (int32_t nmat, const void ** data,
                                                    int data_type, int32_t * nrow,
                                                    int32_t ncol, int is_row_major,
                                                    const char * parameters,
                                                    const DatasetHandle reference,
                                                    DatasetHandle * out)
```

Create dataset from array of dense matrices.

Return 0 when succeed, -1 when failure happens

Parameters

- *nmat*: Number of dense matrices
- *data*: Pointer to the data space
- *data_type*: Type of data pointer, can be C_API_DTYPE_FLOAT32 or C_API_DTYPE_FLOAT64
- *nrow*: Number of rows
- *ncol*: Number of columns
- *is_row_major*: 1 for row-major, 0 for column-major
- *parameters*: Additional parameters
- *reference*: Used to align bin mapper with other dataset, nullptr means isn't used
- [*out*] *out*: Created dataset

```
LIGHTGBM_C_EXPORT int LGBM_DatasetCreateFromSampledColumn (double ** sample_data,
                                                             int ** sample_indices,
                                                             int32_t ncol, const
                                                             int * num_per_col,
                                                             int32_t num_sample_row,
                                                             int32_t num_total_row,
                                                             const char * parameters,
                                                             DatasetHandle * out)
```

Allocate the space for dataset and bucket feature bins according to sampled data.

Return 0 when succeed, -1 when failure happens

Parameters

- *sample_data*: Sampled data, grouped by the column
- *sample_indices*: Indices of sampled data
- *ncol*: Number of columns
- *num_per_col*: Size of each sampling column
- *num_sample_row*: Number of sampled rows
- *num_total_row*: Number of total rows
- *parameters*: Additional parameters
- [*out*] *out*: Created dataset

```
LIGHTGBM_C_EXPORT int LGBM_DatasetDumpText (DatasetHandle handle, const char * filename)
```

Save dataset to text file, intended for debugging use only.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of dataset
- filename: The name of the file

LIGHTGBM_C_EXPORT int **LGBM_DatasetFree** (*DatasetHandle* handle)

Free space for dataset.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of dataset to be freed

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetFeatureNames** (*DatasetHandle* handle,
char ** feature_names, int
* num_feature_names)

Get feature names of dataset.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of dataset
- [out] feature_names: Feature names, should pre-allocate memory
- [out] num_feature_names: Number of feature names

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetField** (*DatasetHandle* handle, const char * field_name,
int * out_len, const void ** out_ptr, int
* out_type)

Get info vector from dataset.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of dataset
- field_name: Field name
- [out] out_len: Used to set result length
- [out] out_ptr: Pointer to the result
- [out] out_type: Type of result pointer, can be C_API_DTYPE_INT8, C_API_DTYPE_INT32, C_API_DTYPE_FLOAT32 or C_API_DTYPE_FLOAT64

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetNumData** (*DatasetHandle* handle, int * out)

Get number of data points.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of dataset
- [out] out: The address to hold number of data points

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetNumFeature** (*DatasetHandle* handle, int * out)

Get number of features.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of dataset
- [out] out: The address to hold number of features

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetSubset** (const *DatasetHandle* handle,
const int32_t * used_row_indices,
int32_t num_used_row_indices, const char
* parameters, *DatasetHandle* * out)

Create subset of a data.

Return 0 when succeed, -1 when failure happens

Parameters

- handle: Handle of full dataset
- used_row_indices: Indices used in subset
- num_used_row_indices: Length of used_row_indices
- parameters: Additional parameters
- [out] out: Subset of data

LIGHTGBM_C_EXPORT int **LGBM_DatasetPushRows** (*DatasetHandle* dataset, const void * data,
int data_type, int32_t nrow, int32_t ncol,
int32_t start_row)

Push data to existing dataset, if nrow + start_row == num_total_row, will call dataset->FinishLoad.

Return 0 when succeed, -1 when failure happens

Parameters

- dataset: Handle of dataset
- data: Pointer to the data space
- data_type: Type of data pointer, can be C_API_DTYPE_FLOAT32 or C_API_DTYPE_FLOAT64
- nrow: Number of rows
- ncol: Number of columns
- start_row: Row start index

LIGHTGBM_C_EXPORT int **LGBM_DatasetPushRowsByCSR** (*DatasetHandle* dataset, const void * indptr,
int indptr_type, const int32_t * indices, const void * data, int data_type,
int64_t nindptr, int64_t nelem,
int64_t num_col, int64_t start_row)

Push data to existing dataset, if nrow + start_row == num_total_row, will call dataset->FinishLoad.

Return 0 when succeed, -1 when failure happens

Parameters

- `dataset`: Handle of dataset
- `indptr`: Pointer to row headers
- `indptr_type`: Type of `indptr`, can be `C_API_DTYPE_INT32` or `C_API_DTYPE_INT64`
- `indices`: Pointer to column indices
- `data`: Pointer to the data space
- `data_type`: Type of data pointer, can be `C_API_DTYPE_FLOAT32` or `C_API_DTYPE_FLOAT64`
- `nindptr`: Number of rows in the matrix + 1
- `nelem`: Number of nonzero elements in the matrix
- `num_col`: Number of columns
- `start_row`: Row start index

`LIGHTGBM_C_EXPORT int LGBM_DatasetSaveBinary` (*DatasetHandle* `handle`, `const char * filename`)
Save dataset to binary file.

Return 0 when succeed, -1 when failure happens

Parameters

- `handle`: Handle of dataset
- `filename`: The name of the file

`LIGHTGBM_C_EXPORT int LGBM_DatasetSetFeatureNames` (*DatasetHandle* `handle`, `const char ** feature_names`,
`int num_feature_names`)

Save feature names to dataset.

Return 0 when succeed, -1 when failure happens

Parameters

- `handle`: Handle of dataset
- `feature_names`: Feature names
- `num_feature_names`: Number of feature names

`LIGHTGBM_C_EXPORT int LGBM_DatasetSetField` (*DatasetHandle* `handle`, `const char * field_name`,
`const void * field_data`, `int num_element`,
`int type`)

Set vector to a content in info.

Note

- *group* only works for `C_API_DTYPE_INT32`;
- *label* and *weight* only work for `C_API_DTYPE_FLOAT32`;
- *init_score* only works for `C_API_DTYPE_FLOAT64`.

Return 0 when succeed, -1 when failure happens

Parameters

- `handle`: Handle of dataset
- `field_name`: Field name, can be *label*, *weight*, *init_score*, *group*
- `field_data`: Pointer to data vector
- `num_element`: Number of elements in `field_data`
- `type`: Type of `field_data` pointer, can be `C_API_DTYPE_INT32`, `C_API_DTYPE_FLOAT32` or `C_API_DTYPE_FLOAT64`

`LIGHTGBM_C_EXPORT int LGBM_DatasetUpdateParam` (*DatasetHandle* `handle`, `const char * parameters`)

Update parameters for a dataset.

Parameters

- `handle`: Handle of dataset
- `parameters`: Parameters

`LIGHTGBM_C_EXPORT const char* LGBM_GetLastError` ()

Get string message of the last error.

Return Error information

`LIGHTGBM_C_EXPORT int LGBM_NetworkFree` ()

Finalize the network.

Return 0 when succeed, -1 when failure happens

`LIGHTGBM_C_EXPORT int LGBM_NetworkInit` (`const char * machines`, `int local_listen_port`, `int listen_time_out`, `int num_machines`)

Initialize the network.

Return 0 when succeed, -1 when failure happens

Parameters

- `machines`: List of machines in format 'ip1:port1,ip2:port2'
- `local_listen_port`: TCP listen port for local machines
- `listen_time_out`: Socket time-out in minutes
- `num_machines`: Total number of machines

`LIGHTGBM_C_EXPORT int LGBM_NetworkInitWithFunctions` (`int num_machines`, `int rank`, `void * reduce_scatter_ext_fun`, `void * allgather_ext_fun`)

Initialize the network with external collective functions.

Return 0 when succeed, -1 when failure happens

Parameters

- `num_machines`: Total number of machines
- `rank`: Rank of local machine
- `reduce_scatter_ext_fun`: The external reduce-scatter function
- `allgather_ext_fun`: The external allgather function

void **LGBM_SetLastError** (const char * *msg*)
Set string message of the last error.

Parameters

- *msg*: Error message

9.1 Data Structure API

| | |
|---|----------------------|
| <code>Dataset(data[, label, reference, weight, ...])</code> | Dataset in LightGBM. |
| <code>Booster([params, train_set, model_file, ...])</code> | Booster in LightGBM. |

9.1.1 `lightgbm.Dataset`

```
class lightgbm.Dataset(data, label=None, reference=None, weight=None, group=None,
                        init_score=None, silent=False, feature_name='auto', categorical_feature='auto',
                        params=None, free_raw_data=True)
```

Bases: object

Dataset in LightGBM.

```
__init__(data, label=None, reference=None, weight=None, group=None, init_score=None,
          silent=False, feature_name='auto', categorical_feature='auto', params=None,
          free_raw_data=True)
```

Initialize Dataset.

Parameters

- **data** (string, numpy array, pandas DataFrame, H2O DataTable's Frame, scipy.sparse or list of numpy arrays) – Data source of Dataset. If string, it represents the path to txt file.
- **label** (list, numpy 1-D array, pandas Series / one-column DataFrame or None, optional (default=None)) – Label of the data.
- **reference** (Dataset or None, optional (default=None)) – If this is Dataset for validation, training data should be used as reference.
- **weight** (list, numpy 1-D array, pandas Series or None, optional (default=None)) – Weight for each instance.

- **group** (*list, numpy 1-D array, pandas Series or None, optional (default=None)*) – Group/query size for Dataset.
- **init_score** (*list, numpy 1-D array, pandas Series or None, optional (default=None)*) – Init score for Dataset.
- **silent** (*bool, optional (default=False)*) – Whether to print messages during construction.
- **feature_name** (*list of strings or 'auto', optional (default="auto")*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of strings or int, or 'auto', optional (default="auto")*) – Categorical features. If list of int, interpreted as indices. If list of strings, interpreted as feature names (need to specify feature_name as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature.
- **params** (*dict or None, optional (default=None)*) – Other parameters for Dataset.
- **free_raw_data** (*bool, optional (default=True)*) – If True, raw data is freed after constructing inner Dataset.

Methods

| | |
|--|---|
| <code>__init__(data[, label, reference, weight, ...])</code> | Initialize Dataset. |
| <code>add_features_from(other)</code> | Add features from other Dataset to the current Dataset. |
| <code>construct()</code> | Lazy init. |
| <code>create_valid(data[, label, weight, group, ...])</code> | Create validation data align with current Dataset. |
| <code>get_data()</code> | Get the raw data of the Dataset. |
| <code>get_feature_penalty()</code> | Get the feature penalty of the Dataset. |
| <code>get_field(field_name)</code> | Get property from the Dataset. |
| <code>get_group()</code> | Get the group of the Dataset. |
| <code>get_init_score()</code> | Get the initial score of the Dataset. |
| <code>get_label()</code> | Get the label of the Dataset. |
| <code>get_monotone_constraints()</code> | Get the monotone constraints of the Dataset. |
| <code>get_ref_chain([ref_limit])</code> | Get a chain of Dataset objects. |
| <code>get_weight()</code> | Get the weight of the Dataset. |
| <code>num_data()</code> | Get the number of rows in the Dataset. |
| <code>num_feature()</code> | Get the number of columns (features) in the Dataset. |
| <code>save_binary(filename)</code> | Save Dataset to a binary file. |
| <code>set_categorical_feature(categorical_feature)</code> | Set categorical features. |
| <code>set_feature_name(feature_name)</code> | Set feature name. |
| <code>set_field(field_name, data)</code> | Set property into the Dataset. |
| <code>set_group(group)</code> | Set group size of Dataset (used for ranking). |
| <code>set_init_score(init_score)</code> | Set init score of Booster to start from. |
| <code>set_label(label)</code> | Set label of Dataset. |

Continued on next page

Table 2 – continued from previous page

| | |
|---|--------------------------------|
| <code>set_reference(reference)</code> | Set reference Dataset. |
| <code>set_weight(weight)</code> | Set weight of each instance. |
| <code>subset(used_indices[, params])</code> | Get subset of current Dataset. |

add_features_from (*other*)

Add features from other Dataset to the current Dataset.

Both Datasets must be constructed before calling this method.

Parameters *other* (*Dataset*) – The Dataset to take features from.

Returns *self* – Dataset with the new features added.

Return type *Dataset*

construct ()

Lazy init.

Returns *self* – Constructed Dataset object.

Return type *Dataset*

create_valid (*data*, *label=None*, *weight=None*, *group=None*, *init_score=None*, *silent=False*, *params=None*)

Create validation data align with current Dataset.

Parameters

- **data** (*string*, *numpy array*, *pandas DataFrame*, *H2O DataTable's Frame*, *scipy.sparse* or *list of numpy arrays*) – Data source of Dataset. If string, it represents the path to txt file.
- **label** (*list*, *numpy 1-D array*, *pandas Series* / *one-column DataFrame* or *None*, *optional (default=None)*) – Label of the data.
- **weight** (*list*, *numpy 1-D array*, *pandas Series* or *None*, *optional (default=None)*) – Weight for each instance.
- **group** (*list*, *numpy 1-D array*, *pandas Series* or *None*, *optional (default=None)*) – Group/query size for Dataset.
- **init_score** (*list*, *numpy 1-D array*, *pandas Series* or *None*, *optional (default=None)*) – Init score for Dataset.
- **silent** (*bool*, *optional (default=False)*) – Whether to print messages during construction.
- **params** (*dict* or *None*, *optional (default=None)*) – Other parameters for validation Dataset.

Returns *valid* – Validation Dataset with reference to self.

Return type *Dataset*

get_data ()

Get the raw data of the Dataset.

Returns *data* – Raw data used in the Dataset construction.

Return type *string*, *numpy array*, *pandas DataFrame*, *H2O DataTable's Frame*, *scipy.sparse*, *list of numpy arrays* or *None*

get_feature_penalty ()

Get the feature penalty of the Dataset.

Returns `feature_penalty` – Feature penalty for each feature in the Dataset.

Return type numpy array or None

get_field (*field_name*)

Get property from the Dataset.

Parameters `field_name` (*string*) – The field name of the information.

Returns `info` – A numpy array with information from the Dataset.

Return type numpy array

get_group ()

Get the group of the Dataset.

Returns `group` – Group size of each group.

Return type numpy array or None

get_init_score ()

Get the initial score of the Dataset.

Returns `init_score` – Init score of Booster.

Return type numpy array or None

get_label ()

Get the label of the Dataset.

Returns `label` – The label information from the Dataset.

Return type numpy array or None

get_monotone_constraints ()

Get the monotone constraints of the Dataset.

Returns `monotone_constraints` – Monotone constraints: -1, 0 or 1, for each feature in the Dataset.

Return type numpy array or None

get_ref_chain (*ref_limit=100*)

Get a chain of Dataset objects.

Starts with `r`, then goes to `r.reference` (if exists), then to `r.reference.reference`, etc. until we hit `ref_limit` or a reference loop.

Parameters `ref_limit` (*int, optional (default=100)*) – The limit number of references.

Returns `ref_chain` – Chain of references of the Datasets.

Return type set of Dataset

get_weight ()

Get the weight of the Dataset.

Returns `weight` – Weight for each data point from the Dataset.

Return type numpy array or None

num_data ()

Get the number of rows in the Dataset.

Returns `number_of_rows` – The number of rows in the Dataset.

Return type int

num_feature ()

Get the number of columns (features) in the Dataset.

Returns **number_of_columns** – The number of columns (features) in the Dataset.

Return type `int`

save_binary (*filename*)

Save Dataset to a binary file.

Parameters **filename** (*string*) – Name of the output file.

Returns **self** – Returns self.

Return type *Dataset*

set_categorical_feature (*categorical_feature*)

Set categorical features.

Parameters **categorical_feature** (*list of int or strings*) – Names or indices of categorical features.

Returns **self** – Dataset with set categorical features.

Return type *Dataset*

set_feature_name (*feature_name*)

Set feature name.

Parameters **feature_name** (*list of strings*) – Feature names.

Returns **self** – Dataset with set feature name.

Return type *Dataset*

set_field (*field_name, data*)

Set property into the Dataset.

Parameters

- **field_name** (*string*) – The field name of the information.
- **data** (*list, numpy 1-D array, pandas Series or None*) – The array of data to be set.

Returns **self** – Dataset with set property.

Return type *Dataset*

set_group (*group*)

Set group size of Dataset (used for ranking).

Parameters **group** (*list, numpy 1-D array, pandas Series or None*) – Group size of each group.

Returns **self** – Dataset with set group.

Return type *Dataset*

set_init_score (*init_score*)

Set init score of Booster to start from.

Parameters **init_score** (*list, numpy 1-D array, pandas Series or None*) – Init score for Booster.

Returns **self** – Dataset with set init score.

Return type *Dataset*

set_label (*label*)

Set label of Dataset.

Parameters **label** (*list, numpy 1-D array, pandas Series / one-column DataFrame or None*) – The label information to be set into Dataset.

Returns **self** – Dataset with set label.

Return type *Dataset*

set_reference (*reference*)

Set reference Dataset.

Parameters **reference** (*Dataset*) – Reference that is used as a template to construct the current Dataset.

Returns **self** – Dataset with set reference.

Return type *Dataset*

set_weight (*weight*)

Set weight of each instance.

Parameters **weight** (*list, numpy 1-D array, pandas Series or None*) – Weight to be set for each data point.

Returns **self** – Dataset with set weight.

Return type *Dataset*

subset (*used_indices, params=None*)

Get subset of current Dataset.

Parameters

- **used_indices** (*list of int*) – Indices used to create the subset.
- **params** (*dict or None, optional (default=None)*) – These parameters will be passed to Dataset constructor.

Returns **subset** – Subset of the current Dataset.

Return type *Dataset*

9.1.2 lightgbm.Booster

class lightgbm.Booster (*params=None, train_set=None, model_file=None, model_str=None, silent=False*)

Bases: object

Booster in LightGBM.

__init__ (*params=None, train_set=None, model_file=None, model_str=None, silent=False*)

Initialize the Booster.

Parameters

- **params** (*dict or None, optional (default=None)*) – Parameters for Booster.
- **train_set** (*Dataset or None, optional (default=None)*) – Training dataset.
- **model_file** (*string or None, optional (default=None)*) – Path to the model file.

- **model_str** (*string or None, optional (default=None)*) – Model will be loaded from this string.
- **silent** (*bool, optional (default=False)*) – Whether to print messages during construction.

Methods

| | |
|--|--|
| <code>__init__([params, train_set, model_file, ...])</code> | Initialize the Booster. |
| <code>add_valid(data, name)</code> | Add validation data. |
| <code>attr(key)</code> | Get attribute string from the Booster. |
| <code>current_iteration()</code> | Get the index of the current iteration. |
| <code>dump_model([num_iteration, start_iteration])</code> | Dump Booster to JSON format. |
| <code>eval(data, name[, feval])</code> | Evaluate for data. |
| <code>eval_train([feval])</code> | Evaluate for training data. |
| <code>eval_valid([feval])</code> | Evaluate for validation data. |
| <code>feature_importance([importance_type, iteration])</code> | Get feature importances. |
| <code>feature_name()</code> | Get names of features. |
| <code>free_dataset()</code> | Free Booster's Datasets. |
| <code>free_network()</code> | Free Booster's network. |
| <code>get_leaf_output(tree_id, leaf_id)</code> | Get the output of a leaf. |
| <code>get_split_value_histogram(feature[, bins, ...])</code> | Get split value histogram for the specified feature. |
| <code>model_from_string(model_str[, verbose])</code> | Load Booster from a string. |
| <code>model_to_string([num_iteration, start_iteration])</code> | Save Booster to string. |
| <code>num_feature()</code> | Get number of features. |
| <code>num_model_per_iteration()</code> | Get number of models per iteration. |
| <code>num_trees()</code> | Get number of weak sub-models. |
| <code>predict(data[, num_iteration, raw_score, ...])</code> | Make a prediction. |
| <code>refit(data, label[, decay_rate])</code> | Refit the existing Booster by new data. |
| <code>reset_parameter(params)</code> | Reset parameters of Booster. |
| <code>rollback_one_iter()</code> | Rollback one iteration. |
| <code>save_model(filename[, num_iteration, ...])</code> | Save Booster to file. |
| <code>set_attr(**kwargs)</code> | Set attributes to the Booster. |
| <code>set_network(machines[, local_listen_port, ...])</code> | Set the network configuration. |
| <code>set_train_data_name(name)</code> | Set the name to the training Dataset. |
| <code>shuffle_models([start_iteration, end_iteration])</code> | Shuffle models. |
| <code>update([train_set, fobj])</code> | Update Booster for one iteration. |

add_valid (*data, name*)

Add validation data.

Parameters

- **data** (*Dataset*) – Validation data.
- **name** (*string*) – Name of validation data.

Returns **self** – Booster with set validation data.

Return type *Booster*

attr (*key*)

Get attribute string from the Booster.

Parameters **key** (*string*) – The name of the attribute.

Returns **value** – The attribute value. Returns None if attribute does not exist.

Return type string or None

current_iteration ()

Get the index of the current iteration.

Returns **cur_iter** – The index of the current iteration.

Return type int

dump_model (*num_iteration=None, start_iteration=0*)

Dump Booster to JSON format.

Parameters

- **num_iteration** (*int or None, optional (default=None)*) – Index of the iteration that should be dumped. If None, if the best iteration exists, it is dumped; otherwise, all iterations are dumped. If ≤ 0 , all iterations are dumped.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration that should be dumped.

Returns **json_repr** – JSON format of Booster.

Return type dict

eval (*data, name, feval=None*)

Evaluate for data.

Parameters

- **data** (*Dataset*) – Data for the evaluating.
- **name** (*string*) – Name of the data.
- **feval** (*callable or None, optional (default=None)*) – Customized evaluation function. Should accept two parameters: **preds**, **eval_data**, and return (**eval_name**, **eval_result**, **is_higher_better**) or list of such tuples.

preds [list or numpy 1-D array] The predicted values.

eval_data [*Dataset*] The evaluation dataset.

eval_name [string] The name of evaluation function (without whitespaces).

eval_result [float] The eval result.

is_higher_better [bool] Is eval result higher better, e.g. AUC is **is_higher_better**.

For multi-class task, the **preds** is group by **class_id** first, then group by **row_id**. If you want to get *i*-th row **preds** in *j*-th class, the access way is **preds**[*j* * **num_data** + *i*].

Returns **result** – List with evaluation results.

Return type list

eval_train (*feval=None*)

Evaluate for training data.

Parameters **feval** (*callable or None, optional (default=None)*) – Customized evaluation function. Should accept two parameters: preds, train_data, and return (eval_name, eval_result, is_higher_better) or list of such tuples.

preds [list or numpy 1-D array] The predicted values.

train_data [Dataset] The training dataset.

eval_name [string] The name of evaluation function (without whitespaces).

eval_result [float] The eval result.

is_higher_better [bool] Is eval result higher better, e.g. AUC is is_higher_better.

For multi-class task, the preds is group by class_id first, then group by row_id. If you want to get i-th row preds in j-th class, the access way is preds[j * num_data + i].

Returns **result** – List with evaluation results.

Return type list

eval_valid (*feval=None*)
Evaluate for validation data.

Parameters **feval** (*callable or None, optional (default=None)*) – Customized evaluation function. Should accept two parameters: preds, valid_data, and return (eval_name, eval_result, is_higher_better) or list of such tuples.

preds [list or numpy 1-D array] The predicted values.

valid_data [Dataset] The validation dataset.

eval_name [string] The name of evaluation function (without whitespaces).

eval_result [float] The eval result.

is_higher_better [bool] Is eval result higher better, e.g. AUC is is_higher_better.

For multi-class task, the preds is group by class_id first, then group by row_id. If you want to get i-th row preds in j-th class, the access way is preds[j * num_data + i].

Returns **result** – List with evaluation results.

Return type list

feature_importance (*importance_type='split', iteration=None*)
Get feature importances.

Parameters

- **importance_type** (*string, optional (default="split")*) – How the importance is calculated. If “split”, result contains numbers of times the feature is used in a model. If “gain”, result contains total gains of splits which use the feature.
- **iteration** (*int or None, optional (default=None)*) – Limit number of iterations in the feature importance calculation. If None, if the best iteration exists, it is used; otherwise, all trees are used. If <= 0, all trees are used (no limits).

Returns **result** – Array with feature importances.

Return type numpy array

feature_name()

Get names of features.

Returns result – List with names of features.

Return type list

free_dataset()

Free Booster's Datasets.

Returns self – Booster without Datasets.

Return type *Booster*

free_network()

Free Booster's network.

Returns self – Booster with freed network.

Return type *Booster*

get_leaf_output(*tree_id*, *leaf_id*)

Get the output of a leaf.

Parameters

- **tree_id** (*int*) – The index of the tree.
- **leaf_id** (*int*) – The index of the leaf in the tree.

Returns result – The output of the leaf.

Return type float

get_split_value_histogram(*feature*, *bins*=None, *xgboost_style*=False)

Get split value histogram for the specified feature.

Parameters

- **feature** (*int* or *string*) – The feature name or index the histogram is calculated for. If int, interpreted as index. If string, interpreted as name.

Warning: Categorical features are not supported.

- **bins** (*int*, *string* or *None*, *optional* (*default*=None)) – The maximum number of bins. If None, or int and > number of unique split values and *xgboost_style*=True, the number of bins equals number of unique split values. If string, it should be one from the list of the supported values by `numpy.histogram()` function.
- **xgboost_style** (*bool*, *optional* (*default*=False)) – Whether the returned result should be in the same form as it is in XGBoost. If False, the returned value is tuple of 2 numpy arrays as it is in `numpy.histogram()` function. If True, the returned value is matrix, in which the first column is the right edges of non-empty bins and the second one is the histogram values.

Returns

- **result_tuple** (*tuple of 2 numpy arrays*) – If *xgboost_style*=False, the values of the histogram of used splitting values for the specified feature and the bin edges.

- **result_array_like** (*numpy array or pandas DataFrame (if pandas is installed)*) – If `xgboost_style=True`, the histogram of used splitting values for the specified feature.

model_from_string (*model_str, verbose=True*)

Load Booster from a string.

Parameters

- **model_str** (*string*) – Model will be loaded from this string.
- **verbose** (*bool, optional (default=True)*) – Whether to print messages while loading model.

Returns `self` – Loaded Booster object.

Return type *Booster*

model_to_string (*num_iteration=None, start_iteration=0*)

Save Booster to string.

Parameters

- **num_iteration** (*int or None, optional (default=None)*) – Index of the iteration that should be saved. If `None`, if the best iteration exists, it is saved; otherwise, all iterations are saved. If `<= 0`, all iterations are saved.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration that should be saved.

Returns `str_repr` – String representation of Booster.

Return type `string`

num_feature ()

Get number of features.

Returns `num_feature` – The number of features.

Return type `int`

num_model_per_iteration ()

Get number of models per iteration.

Returns `model_per_iter` – The number of models per iteration.

Return type `int`

num_trees ()

Get number of weak sub-models.

Returns `num_trees` – The number of weak sub-models.

Return type `int`

predict (*data, num_iteration=None, raw_score=False, pred_leaf=False, pred_contrib=False, data_has_header=False, is_reshape=True, **kwargs*)

Make a prediction.

Parameters

- **data** (*string, numpy array, pandas DataFrame, H2O DataTable's Frame or scipy.sparse*) – Data source for prediction. If string, it represents the path to txt file.

- **num_iteration** (*int or None, optional (default=None)*) – Limit number of iterations in the prediction. If None, if the best iteration exists, it is used; otherwise, all iterations are used. If ≤ 0 , all iterations are used (no limits).
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

Note: If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (<https://github.com/slundberg/shap>). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **data_has_header** (*bool, optional (default=False)*) – Whether the data has header. Used only if data is string.
- **is_reshape** (*bool, optional (default=True)*) – If True, result is reshaped to [nrow, ncol].
- ****kwargs** – Other parameters for the prediction.

Returns **result** – Prediction result.

Return type numpy array

refit (*data, label, decay_rate=0.9, **kwargs*)
Refit the existing Booster by new data.

Parameters

- **data** (*string, numpy array, pandas DataFrame, H2O DataTable's Frame or scipy.sparse*) – Data source for refit. If string, it represents the path to txt file.
- **label** (*list, numpy 1-D array or pandas Series / one-column DataFrame*) – Label for refit.
- **decay_rate** (*float, optional (default=0.9)*) – Decay rate of refit, will use $\text{leaf_output} = \text{decay_rate} * \text{old_leaf_output} + (1.0 - \text{decay_rate}) * \text{new_leaf_output}$ to refit trees.
- ****kwargs** – Other parameters for refit. These parameters will be passed to predict method.

Returns **result** – Refitted Booster.

Return type *Booster*

reset_parameter (*params*)
Reset parameters of Booster.

Parameters **params** (*dict*) – New parameters for Booster.

Returns **self** – Booster with new parameters.

Return type *Booster*

rollback_one_iter()

Rollback one iteration.

Returns self – Booster with rolled back one iteration.

Return type *Booster*

save_model (*filename*, *num_iteration=None*, *start_iteration=0*)

Save Booster to file.

Parameters

- **filename** (*string*) – Filename to save Booster.
- **num_iteration** (*int or None, optional (default=None)*) – Index of the iteration that should be saved. If None, if the best iteration exists, it is saved; otherwise, all iterations are saved. If ≤ 0 , all iterations are saved.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration that should be saved.

Returns self – Returns self.

Return type *Booster*

set_attr (***kwargs*)

Set attributes to the Booster.

Parameters ****kwargs** – The attributes to set. Setting a value to None deletes an attribute.

Returns self – Booster with set attributes.

Return type *Booster*

set_network (*machines*, *local_listen_port=12400*, *listen_time_out=120*, *num_machines=1*)

Set the network configuration.

Parameters

- **machines** (*list, set or string*) – Names of machines.
- **local_listen_port** (*int, optional (default=12400)*) – TCP listen port for local machines.
- **listen_time_out** (*int, optional (default=120)*) – Socket time-out in minutes.
- **num_machines** (*int, optional (default=1)*) – The number of machines for parallel learning application.

Returns self – Booster with set network.

Return type *Booster*

set_train_data_name (*name*)

Set the name to the training Dataset.

Parameters **name** (*string*) – Name for the training Dataset.

Returns self – Booster with set training Dataset name.

Return type *Booster*

shuffle_models (*start_iteration=0*, *end_iteration=-1*)

Shuffle models.

Parameters

- **start_iteration** (*int, optional (default=0)*) – The first iteration that will be shuffled.
- **end_iteration** (*int, optional (default=-1)*) – The last iteration that will be shuffled. If ≤ 0 , means the last available iteration.

Returns **self** – Booster with shuffled models.

Return type *Booster*

update (*train_set=None, fobj=None*)
Update Booster for one iteration.

Parameters

- **train_set** (*Dataset or None, optional (default=None)*) – Training data. If None, last training data is used.
- **fobj** (*callable or None, optional (default=None)*) – Customized objective function. Should accept two parameters: preds, train_data, and return (grad, hess).

preds [list or numpy 1-D array] The predicted values.

train_data [Dataset] The training dataset.

grad [list or numpy 1-D array] The value of the first order derivative (gradient) for each sample point.

hess [list or numpy 1-D array] The value of the second order derivative (Hessian) for each sample point.

For multi-class task, the preds is group by class_id first, then group by row_id. If you want to get i-th row preds in j-th class, the access way is `score[j * num_data + i]` and you should group grad and hess in this way as well.

Returns **is_finished** – Whether the update was successfully finished.

Return type **bool**

9.2 Training API

| | |
|---|---|
| <code>train(params, train_set[, num_boost_round, ...])</code> | Perform the training with given parameters. |
| <code>cv(params, train_set[, num_boost_round, ...])</code> | Perform the cross-validation with given parameters. |

9.2.1 lightgbm.train

`lightgbm.train` (*params, train_set, num_boost_round=100, valid_sets=None, valid_names=None, fobj=None, feval=None, init_model=None, feature_name='auto', categorical_feature='auto', early_stopping_rounds=None, evals_result=None, verbose_eval=True, learning_rates=None, keep_training_booster=False, callbacks=None*)

Perform the training with given parameters.

Parameters

- **params** (*dict*) – Parameters for training.
- **train_set** (*Dataset*) – Data to be trained on.

- **num_boost_round** (*int, optional (default=100)*) – Number of boosting iterations.
- **valid_sets** (*(list of Datasets or None, optional (default=None))*) – List of data to be evaluated on during training.
- **valid_names** (*(list of strings or None, optional (default=None))*) – Names of `valid_sets`.
- **fobj** (*callable or None, optional (default=None)*) – Customized objective function. Should accept two parameters: `preds`, `train_data`, and return (`grad`, `hess`).

preds [list or numpy 1-D array] The predicted values.

train_data [Dataset] The training dataset.

grad [list or numpy 1-D array] The value of the first order derivative (gradient) for each sample point.

hess [list or numpy 1-D array] The value of the second order derivative (Hessian) for each sample point.

For multi-class task, the `preds` is group by `class_id` first, then group by `row_id`. If you want to get *i*-th row `preds` in *j*-th class, the access way is `score[j * num_data + i]` and you should group `grad` and `hess` in this way as well.

- **feval** (*callable or None, optional (default=None)*) – Customized evaluation function. Should accept two parameters: `preds`, `train_data`, and return (`eval_name`, `eval_result`, `is_higher_better`) or list of such tuples.

preds [list or numpy 1-D array] The predicted values.

train_data [Dataset] The training dataset.

eval_name [string] The name of evaluation function (without whitespaces).

eval_result [float] The eval result.

is_higher_better [bool] Is eval result higher better, e.g. AUC is `is_higher_better`.

For multi-class task, the `preds` is group by `class_id` first, then group by `row_id`. If you want to get *i*-th row `preds` in *j*-th class, the access way is `preds[j * num_data + i]`. To ignore the default metric corresponding to the used objective, set the `metric` parameter to the string "None" in `params`.

- **init_model** (*(string, Booster or None, optional (default=None))*) – Filename of LightGBM model or Booster instance used for continue training.
- **feature_name** (*(list of strings or 'auto', optional (default="auto"))*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*(list of strings or int, or 'auto', optional (default="auto"))*) – Categorical features. If list of int, interpreted as indices. If list of strings, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature.

- **early_stopping_rounds** (*int or None, optional (default=None)*) – Activates early stopping. The model will train until the validation score stops improving. Validation score needs to improve at least every `early_stopping_rounds` round(s) to continue training. Requires at least one validation data and one metric. If there's more than one, will check all of them. But the training data is ignored anyway. To check only the first metric, set the `first_metric_only` parameter to `True` in `params`. The index of iteration that has the best performance will be saved in the `best_iteration` field if early stopping logic is enabled by setting `early_stopping_rounds`.
- **evals_result** (*dict or None, optional (default=None)*) – This dictionary used to store all evaluation results of all the items in `valid_sets`.

Example

With a `valid_sets = [valid_set, train_set]`, `valid_names = ['eval', 'train']` and a `params = {'metric': 'logloss'}` returns `{ 'train': { 'logloss': ['0.48253', '0.35953', ...] }, 'eval': { 'logloss': ['0.480385', '0.357756', ...] } }`.

- **verbose_eval** (*bool or int, optional (default=True)*) – Requires at least one validation data. If `True`, the eval metric on the valid set is printed at each boosting stage. If `int`, the eval metric on the valid set is printed at every `verbose_eval` boosting stage. The last boosting stage or the boosting stage found by using `early_stopping_rounds` is also printed.

Example

With `verbose_eval = 4` and at least one item in `valid_sets`, an evaluation metric is printed every 4 (instead of 1) boosting stages.

- **learning_rates** (*list, callable or None, optional (default=None)*) – List of learning rates for each boosting round or a customized function that calculates `learning_rate` in terms of current number of round (e.g. yields learning rate decay).
- **keep_training_booster** (*bool, optional (default=False)*) – Whether the returned Booster will be used to keep training. If `False`, the returned value will be converted into `_InnerPredictor` before returning. You can still use `_InnerPredictor` as `init_model` for future continue training.
- **callbacks** (*list of callables or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.

Returns `booster` – The trained Booster model.

Return type `Booster`

9.2.2 lightgbm.cv

`lightgbm.cv` (`params`, `train_set`, `num_boost_round=100`, `folds=None`, `nfold=5`, `stratified=True`, `shuffle=True`, `metrics=None`, `fobj=None`, `feval=None`, `init_model=None`, `feature_name='auto'`, `categorical_feature='auto'`, `early_stopping_rounds=None`, `fpreproc=None`, `verbose_eval=None`, `show_stdv=True`, `seed=0`, `callbacks=None`, `eval_train_metric=False`)
Perform the cross-validation with given parameters.

Parameters

- **params** (*dict*) – Parameters for Booster.
- **train_set** (*Dataset*) – Data to be trained on.
- **num_boost_round** (*int*, *optional* (*default=100*)) – Number of boosting iterations.
- **folds** (*generator or iterator of (train_idx, test_idx) tuples, scikit-learn splitter object or None, optional* (*default=None*)) – If generator or iterator, it should yield the train and test indices for each fold. If object, it should be one of the scikit-learn splitter classes (<https://scikit-learn.org/stable/modules/classes.html#splitter-classes>) and have `split` method. This argument has highest priority over other data split arguments.
- **nfold** (*int*, *optional* (*default=5*)) – Number of folds in CV.
- **stratified** (*bool*, *optional* (*default=True*)) – Whether to perform stratified sampling.
- **shuffle** (*bool*, *optional* (*default=True*)) – Whether to shuffle before splitting data.
- **metrics** (*string, list of strings or None, optional* (*default=None*)) – Evaluation metrics to be monitored while CV. If not None, the metric in `params` will be overridden.
- **fobj** (*callable or None, optional* (*default=None*)) – Customized objective function. Should accept two parameters: `preds`, `train_data`, and return (`grad`, `hess`).

preds [list or numpy 1-D array] The predicted values.

train_data [Dataset] The training dataset.

grad [list or numpy 1-D array] The value of the first order derivative (gradient) for each sample point.

hess [list or numpy 1-D array] The value of the second order derivative (Hessian) for each sample point.

For multi-class task, the `preds` is group by `class_id` first, then group by `row_id`. If you want to get `i`-th row `preds` in `j`-th class, the access way is `score[j * num_data + i]` and you should group `grad` and `hess` in this way as well.

- **feval** (*callable or None, optional* (*default=None*)) – Customized evaluation function. Should accept two parameters: `preds`, `train_data`, and return (`eval_name`, `eval_result`, `is_higher_better`) or list of such tuples.

preds [list or numpy 1-D array] The predicted values.

train_data [Dataset] The training dataset.

eval_name [string] The name of evaluation function (without whitespaces).

eval_result [float] The eval result.

is_higher_better [bool] Is eval result higher better, e.g. AUC is `is_higher_better`.

For multi-class task, the `preds` is group by `class_id` first, then group by `row_id`. If you want to get `i`-th row `preds` in `j`-th class, the access way is `preds[j * num_data + i]`. To ignore the default metric corresponding to the used objective, set `metrics` to the string "None".

- **init_model** (*string, Booster or None, optional (default=None)*) – Filename of LightGBM model or Booster instance used for continue training.
- **feature_name** (*list of strings or 'auto', optional (default="auto")*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of strings or int, or 'auto', optional (default="auto")*) – Categorical features. If list of int, interpreted as indices. If list of strings, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature.
- **early_stopping_rounds** (*int or None, optional (default=None)*) – Activates early stopping. CV score needs to improve at least every `early_stopping_rounds` round(s) to continue. Requires at least one metric. If there's more than one, will check all of them. To check only the first metric, set the `first_metric_only` parameter to True in params. Last entry in evaluation history is the one from the best iteration.
- **fpreproc** (*callable or None, optional (default=None)*) – Preprocessing function that takes (dtrain, dtest, params) and returns transformed versions of those.
- **verbose_eval** (*bool, int, or None, optional (default=None)*) – Whether to display the progress. If None, progress will be displayed when np.ndarray is returned. If True, progress will be displayed at every boosting stage. If int, progress will be displayed at every given `verbose_eval` boosting stage.
- **show_stdv** (*bool, optional (default=True)*) – Whether to display the standard deviation in progress. Results are not affected by this parameter, and always contain std.
- **seed** (*int, optional (default=0)*) – Seed used to generate the folds (passed to `numpy.random.seed`).
- **callbacks** (*list of callables or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.
- **eval_train_metric** (*bool, optional (default=False)*) – Whether to display the train metric in progress. The score of the metric is calculated again after each training step, so there is some impact on performance.

Returns `eval_hist` – Evaluation history. The dictionary has the following format: {'metric1-mean': [values], 'metric1-stdv': [values], 'metric2-mean': [values], 'metric2-stdv': [values], ...}.

Return type dict

9.3 Scikit-learn API

| | |
|---|--|
| <code>LGBMModel([boosting_type, num_leaves, ...])</code> | Implementation of the scikit-learn API for LightGBM. |
| <code>LGBMClassifier([boosting_type, num_leaves, ...])</code> | LightGBM classifier. |
| <code>LGBMRegressor([boosting_type, num_leaves, ...])</code> | LightGBM regressor. |
| <code>LGBMRanker([boosting_type, num_leaves, ...])</code> | LightGBM ranker. |

9.3.1 lightgbm.LGBMModel

```
class lightgbm.LGBMModel(boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=-1, silent=True, importance_type='split', **kwargs)
```

Bases: object

Implementation of the scikit-learn API for LightGBM.

```
__init__(boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=-1, silent=True, importance_type='split', **kwargs)
```

Construct a gradient boosting model.

Parameters

- **boosting_type** (*string, optional (default='gbdt')*) – 'gbdt', traditional Gradient Boosting Decision Tree. 'dart', Dropouts meet Multiple Additive Regression Trees. 'goss', Gradient-based One-Side Sampling. 'rf', Random Forest.
- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.
- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, ≤ 0 means no limit.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use `callbacks` parameter of `fit` method to shrink/adapt learning rate in training using `reset_parameter` callback. Note, that this will ignore the `learning_rate` argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.
- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*string, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: 'regression' for LGBMRegressor, 'binary' or 'multiclass' for LGBMClassifier, 'lambdarank' for LGBMRanker.
- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form

`{class_label: weight}`. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (<https://scikit-learn.org/stable/modules/calibration.html>) of your model. The 'balanced' mode uses the values of `y` to automatically adjust weights inversely proportional to class frequencies in the input data as $n_samples / (n_classes * np.bincount(y))$. If `None`, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the fit method) if `sample_weight` is specified.

- **min_split_gain** (*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight** (*float, optional (default=1e-3)*) – Minimum sum of instance weight (hessian) needed in a child (leaf).
- **min_child_samples** (*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample** (*float, optional (default=1.)*) – Subsample ratio of the training instance.
- **subsample_freq** (*int, optional (default=0)*) – Frequency of subsample, ≤ 0 means no enable.
- **colsample_bytree** (*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha** (*float, optional (default=0.)*) – L1 regularization term on weights.
- **reg_lambda** (*float, optional (default=0.)*) – L2 regularization term on weights.
- **random_state** (*int or None, optional (default=None)*) – Random number seed. If `None`, default seeds in C++ code will be used.
- **n_jobs** (*int, optional (default=-1)*) – Number of parallel threads.
- **silent** (*bool, optional (default=True)*) – Whether to print messages while running boosting.
- **importance_type** (*string, optional (default='split')*) – The type of feature importance to be filled into `feature_importances_`. If 'split', result contains numbers of times the feature is used in a model. If 'gain', result contains total gains of splits which use the feature.
- ****kwargs** – Other parameters for the model. Check <http://lightgbm.readthedocs.io/en/latest/Parameters.html> for more parameters.

Warning: `**kwargs` is not supported in sklearn, it may cause unexpected issues.

n_features_

The number of features of fitted model.

Type `int`

classes_
The class label array (only for classification problem).
Type array of shape = [n_classes]

n_classes_
The number of classes (only for classification problem).
Type int

best_score_
The best score of fitted model.
Type dict or None

best_iteration_
The best iteration of fitted model if `early_stopping_rounds` has been specified.
Type int or None

objective_
The concrete objective used while fitting this model.
Type string or callable

booster_
The underlying Booster of this model.
Type *Booster*

evals_result_
The evaluation results if `early_stopping_rounds` has been specified.
Type dict or None

feature_importances_
The feature importances (the higher, the more important the feature).
Type array of shape = [n_features]

Note: A custom objective function can be provided for the `objective` parameter. In this case, it should have the signature `objective(y_true, y_pred) -> grad, hess` or `objective(y_true, y_pred, group) -> grad, hess`:

y_true [array-like of shape = [n_samples]] The target values.

y_pred [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values.

group [array-like] Group/query data, used for ranking task.

grad [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the first order derivative (gradient) for each sample point.

hess [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the second order derivative (Hessian) for each sample point.

For multi-class task, the `y_pred` is group by `class_id` first, then group by `row_id`. If you want to get `i`-th row `y_pred` in `j`-th class, the access way is `y_pred[j * num_data + i]` and you should group `grad` and `hess` in this way as well.

Methods

| | |
|--|---|
| <code>__init__([boosting_type, num_leaves, ...])</code> | Construct a gradient boosting model. |
| <code>fit(X, y[, sample_weight, init_score, ...])</code> | Build a gradient boosting model from the training set (X, y). |
| <code>get_params([deep])</code> | Get parameters for this estimator. |
| <code>predict(X[, raw_score, num_iteration, ...])</code> | Return the predicted value for each sample. |
| <code>set_params(**params)</code> | Set the parameters of this estimator. |

Attributes

| | |
|-----------------------------------|---|
| <code>best_iteration_</code> | Get the best iteration of fitted model. |
| <code>best_score_</code> | Get the best score of fitted model. |
| <code>booster_</code> | Get the underlying lightgbm Booster of this model. |
| <code>evals_result_</code> | Get the evaluation results. |
| <code>feature_importances_</code> | Get feature importances. |
| <code>n_features_</code> | Get the number of features of fitted model. |
| <code>objective_</code> | Get the concrete objective used while fitting this model. |

best_iteration_

Get the best iteration of fitted model.

best_score_

Get the best score of fitted model.

booster_

Get the underlying lightgbm Booster of this model.

evals_result_

Get the evaluation results.

feature_importances_

Get feature importances.

Note: Feature importance in sklearn interface used to normalize to 1, it's deprecated after 2.0.4 and is the same as `Booster.feature_importance()` now. `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

fit (*X*, *y*, *sample_weight*=None, *init_score*=None, *group*=None, *eval_set*=None, *eval_names*=None, *eval_sample_weight*=None, *eval_class_weight*=None, *eval_init_score*=None, *eval_group*=None, *eval_metric*=None, *early_stopping_rounds*=None, *verbose*=True, *feature_name*='auto', *categorical_feature*='auto', *callbacks*=None)
Build a gradient boosting model from the training set (X, y).

Parameters

- **X** (array-like or sparse matrix of shape = [*n_samples*, *n_features*]) – Input feature matrix.
- **y** (array-like of shape = [*n_samples*]) – The target values (class labels in classification, real numbers in regression).

- **sample_weight** (*array-like of shape = [n_samples] or None, optional (default=None)*) – Weights of training data.
- **init_score** (*array-like of shape = [n_samples] or None, optional (default=None)*) – Init score of training data.
- **group** (*array-like or None, optional (default=None)*) – Group data of training data.
- **eval_set** (*list or None, optional (default=None)*) – A list of (X, y) tuple pairs to use as validation sets.
- **eval_names** (*list of strings or None, optional (default=None)*) – Names of eval_set.
- **eval_sample_weight** (*list of arrays or None, optional (default=None)*) – Weights of eval data.
- **eval_class_weight** (*list or None, optional (default=None)*) – Class weights of eval data.
- **eval_init_score** (*list of arrays or None, optional (default=None)*) – Init score of eval data.
- **eval_group** (*list of arrays or None, optional (default=None)*) – Group data of eval data.
- **eval_metric** (*string, list of strings, callable or None, optional (default=None)*) – If string, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. In either case, the metric from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.
- **early_stopping_rounds** (*int or None, optional (default=None)*) – Activates early stopping. The model will train until the validation score stops improving. Validation score needs to improve at least every early_stopping_rounds round(s) to continue training. Requires at least one validation data and one metric. If there's more than one, will check all of them. But the training data is ignored anyway. To check only the first metric, set the first_metric_only parameter to True in additional parameters **kwargs of the model constructor.
- **verbose** (*bool or int, optional (default=True)*) – Requires at least one evaluation data. If True, the eval metric on the eval set is printed at each boosting stage. If int, the eval metric on the eval set is printed at every verbose boosting stage. The last boosting stage or the boosting stage found by using early_stopping_rounds is also printed.

Example

With `verbose = 4` and at least one item in `eval_set`, an evaluation metric is printed every 4 (instead of 1) boosting stages.

- **feature_name** (*list of strings or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.

- **categorical_feature** (*list of strings or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of strings, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature.
- **callbacks** (*list of callback functions or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.

Returns self – Returns self.

Return type object

Note: Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`, `func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns (eval_name, eval_result, is_higher_better) or list of (eval_name, eval_result, is_higher_better):

y_true [array-like of shape = [n_samples]] The target values.

y_pred [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values.

weight [array-like of shape = [n_samples]] The weight of samples.

group [array-like] Group/query data, used for ranking task.

eval_name [string] The name of evaluation function (without whitespaces).

eval_result [float] The eval result.

is_higher_better [bool] Is eval result higher better, e.g. AUC is `is_higher_better`.

For multi-class task, the `y_pred` is group by `class_id` first, then group by `row_id`. If you want to get `i`-th row `y_pred` in `j`-th class, the access way is `y_pred[j * num_data + i]`.

get_params (*deep=True*)

Get parameters for this estimator.

Parameters **deep** (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns **params** – Parameter names mapped to their values.

Return type dict

n_features_

Get the number of features of fitted model.

objective_

Get the concrete objective used while fitting this model.

predict (*X, raw_score=False, num_iteration=None, pred_leaf=False, pred_contrib=False, **kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (array-like or sparse matrix of shape = $[n_samples, n_features]$) – Input features matrix.
- **raw_score** (bool, optional (default=False)) – Whether to predict raw scores.
- **num_iteration** (int or None, optional (default=None)) – Limit number of iterations in the prediction. If None, if the best iteration exists, it is used; otherwise, all trees are used. If ≤ 0 , all trees are used (no limits).
- **pred_leaf** (bool, optional (default=False)) – Whether to predict leaf index.
- **pred_contrib** (bool, optional (default=False)) – Whether to predict feature contributions.

Note: If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (<https://github.com/slundberg/shap>). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (array-like of shape = $[n_samples]$ or shape = $[n_samples, n_classes]$) – The predicted values.
- **X_leaves** (array-like of shape = $[n_samples, n_trees]$ or shape = $[n_samples, n_trees * n_classes]$) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (array-like of shape = $[n_samples, n_features + 1]$ or shape = $[n_samples, (n_features + 1) * n_classes]$) – If `pred_contrib=True`, the feature contributions for each sample.

set_params (**params)

Set the parameters of this estimator.

Parameters ****params** – Parameter names with their new values.

Returns **self** – Returns self.

Return type object

9.3.2 lightgbm.LGBMClassifier

```
class lightgbm.LGBMClassifier(boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=-1, silent=True, importance_type='split', **kwargs)
```

Bases: lightgbm.sklearn.LGBMModel, object

LightGBM classifier.

```
__init__(boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1,
         n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None,
         min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsam-
         ple=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0,
         random_state=None, n_jobs=-1, silent=True, importance_type='split', **kwargs)
```

Construct a gradient boosting model.

Parameters

- **boosting_type** (*string, optional (default='gbdt')*) – 'gbdt', traditional Gradient Boosting Decision Tree. 'dart', Dropouts meet Multiple Additive Regression Trees. 'goss', Gradient-based One-Side Sampling. 'rf', Random Forest.
- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.
- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, ≤ 0 means no limit.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use `callbacks` parameter of `fit` method to shrink/adapt learning rate in training using `reset_parameter` callback. Note, that this will ignore the `learning_rate` argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.
- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*string, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: 'regression' for LGBMRegressor, 'binary' or 'multiclass' for LGBMClassifier, 'lambda_rank' for LGBMRanker.
- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form `{class_label: weight}`. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (<https://scikit-learn.org/stable/modules/calibration.html>) of your model. The 'balanced' mode uses the values of `y` to automatically adjust weights inversely proportional to class frequencies in the input data as $n_{\text{samples}} / (n_{\text{classes}} * \text{np.bincount}(y))$. If `None`, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the `fit` method) if `sample_weight` is specified.
- **min_split_gain** (*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight** (*float, optional (default=1e-3)*) – Minimum sum of instance weight (hessian) needed in a child (leaf).
- **min_child_samples** (*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample** (*float, optional (default=1.)*) – Subsample ratio of the training instance.

- **subsample_freq**(*int, optional (default=0)*) – Frequency of subsample, ≤ 0 means no enable.
- **colsample_bytree**(*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha**(*float, optional (default=0.)*) – L1 regularization term on weights.
- **reg_lambda**(*float, optional (default=0.)*) – L2 regularization term on weights.
- **random_state**(*int or None, optional (default=None)*) – Random number seed. If None, default seeds in C++ code will be used.
- **n_jobs**(*int, optional (default=-1)*) – Number of parallel threads.
- **silent**(*bool, optional (default=True)*) – Whether to print messages while running boosting.
- **importance_type**(*string, optional (default='split')*) – The type of feature importance to be filled into `feature_importances_`. If 'split', result contains numbers of times the feature is used in a model. If 'gain', result contains total gains of splits which use the feature.
- ****kwargs** – Other parameters for the model. Check <http://lightgbm.readthedocs.io/en/latest/Parameters.html> for more parameters.

Warning: `**kwargs` is not supported in sklearn, it may cause unexpected issues.

n_features_

The number of features of fitted model.

Type int

classes_

The class label array (only for classification problem).

Type array of shape = [n_classes]

n_classes_

The number of classes (only for classification problem).

Type int

best_score_

The best score of fitted model.

Type dict or None

best_iteration_

The best iteration of fitted model if `early_stopping_rounds` has been specified.

Type int or None

objective_

The concrete objective used while fitting this model.

Type string or callable

booster_

The underlying Booster of this model.

Type *Booster*

evals_result_

The evaluation results if `early_stopping_rounds` has been specified.

Type dict or None

feature_importances_

The feature importances (the higher, the more important the feature).

Type array of shape = [n_features]

Note: A custom objective function can be provided for the `objective` parameter. In this case, it should have the signature `objective(y_true, y_pred) -> grad, hess` or `objective(y_true, y_pred, group) -> grad, hess`:

y_true [array-like of shape = [n_samples]] The target values.

y_pred [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values.

group [array-like] Group/query data, used for ranking task.

grad [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the first order derivative (gradient) for each sample point.

hess [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the second order derivative (Hessian) for each sample point.

For multi-class task, the `y_pred` is group by `class_id` first, then group by `row_id`. If you want to get `i`-th row `y_pred` in `j`-th class, the access way is `y_pred[j * num_data + i]` and you should group `grad` and `hess` in this way as well.

Methods

| | |
|--|--|
| <code>__init__([boosting_type, num_leaves, ...])</code> | Construct a gradient boosting model. |
| <code>fit(X, y[, sample_weight, init_score, ...])</code> | Build a gradient boosting model from the training set (X, y). |
| <code>get_params([deep])</code> | Get parameters for this estimator. |
| <code>predict(X[, raw_score, num_iteration, ...])</code> | Return the predicted value for each sample. |
| <code>predict_proba(X[, raw_score, num_iteration, ...])</code> | Return the predicted probability for each class for each sample. |
| <code>set_params(**params)</code> | Set the parameters of this estimator. |

Attributes

| | |
|-----------------------------------|--|
| <code>best_iteration_</code> | Get the best iteration of fitted model. |
| <code>best_score_</code> | Get the best score of fitted model. |
| <code>booster_</code> | Get the underlying lightgbm Booster of this model. |
| <code>classes_</code> | Get the class label array. |
| <code>evals_result_</code> | Get the evaluation results. |
| <code>feature_importances_</code> | Get feature importances. |
| <code>n_classes_</code> | Get the number of classes. |
| <code>n_features_</code> | Get the number of features of fitted model. |

Continued on next page

Table 9 – continued from previous page

| | |
|--|---|
| <code>objective_</code> | Get the concrete objective used while fitting this model. |
| <code>best_iteration_</code> | Get the best iteration of fitted model. |
| <code>best_score_</code> | Get the best score of fitted model. |
| <code>booster_</code> | Get the underlying lightgbm Booster of this model. |
| <code>classes_</code> | Get the class label array. |
| <code>evals_result_</code> | Get the evaluation results. |
| <code>feature_importances_</code> | Get feature importances. |
| <p>Note: Feature importance in sklearn interface used to normalize to 1, it's deprecated after 2.0.4 and is the same as <code>Booster.feature_importance()</code> now. <code>importance_type</code> attribute is passed to the function to configure the type of importance values to be extracted.</p> | |

fit (*X*, *y*, *sample_weight*=None, *init_score*=None, *eval_set*=None, *eval_names*=None, *eval_sample_weight*=None, *eval_class_weight*=None, *eval_init_score*=None, *eval_metric*=None, *early_stopping_rounds*=None, *verbose*=True, *feature_name*='auto', *categorical_feature*='auto', *callbacks*=None)
Build a gradient boosting model from the training set (*X*, *y*).

Parameters

- **X** (array-like or sparse matrix of shape = [*n_samples*, *n_features*]) – Input feature matrix.
- **y** (array-like of shape = [*n_samples*]) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (array-like of shape = [*n_samples*] or None, optional (default=None)) – Weights of training data.
- **init_score** (array-like of shape = [*n_samples*] or None, optional (default=None)) – Init score of training data.
- **group** (array-like or None, optional (default=None)) – Group data of training data.
- **eval_set** (list or None, optional (default=None)) – A list of (*X*, *y*) tuple pairs to use as validation sets.
- **eval_names** (list of strings or None, optional (default=None)) – Names of eval_set.
- **eval_sample_weight** (list of arrays or None, optional (default=None)) – Weights of eval data.
- **eval_class_weight** (list or None, optional (default=None)) – Class weights of eval data.

- **eval_init_score** *(list of arrays or None, optional (default=None))* – Init score of eval data.
- **eval_group** *(list of arrays or None, optional (default=None))* – Group data of eval data.
- **eval_metric** *(string, list of strings, callable or None, optional (default=None))* – If string, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. In either case, the metric from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.
- **early_stopping_rounds** *(int or None, optional (default=None))* – Activates early stopping. The model will train until the validation score stops improving. Validation score needs to improve at least every early_stopping_rounds round(s) to continue training. Requires at least one validation data and one metric. If there's more than one, will check all of them. But the training data is ignored anyway. To check only the first metric, set the first_metric_only parameter to True in additional parameters ****kwargs** of the model constructor.
- **verbose** *(bool or int, optional (default=True))* – Requires at least one evaluation data. If True, the eval metric on the eval set is printed at each boosting stage. If int, the eval metric on the eval set is printed at every verbose boosting stage. The last boosting stage or the boosting stage found by using early_stopping_rounds is also printed.

Example

With `verbose = 4` and at least one item in `eval_set`, an evaluation metric is printed every 4 (instead of 1) boosting stages.

- **feature_name** *(list of strings or 'auto', optional (default='auto'))* – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** *(list of strings or int, or 'auto', optional (default='auto'))* – Categorical features. If list of int, interpreted as indices. If list of strings, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature.
- **callbacks** *(list of callback functions or None, optional (default=None))* – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.

Returns `self` – Returns self.

Return type object

Note: Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`,

`func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns (eval_name, eval_result, is_higher_better) or list of (eval_name, eval_result, is_higher_better):

y_true [array-like of shape = [n_samples]] The target values.

y_pred [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values.

weight [array-like of shape = [n_samples]] The weight of samples.

group [array-like] Group/query data, used for ranking task.

eval_name [string] The name of evaluation function (without whitespaces).

eval_result [float] The eval result.

is_higher_better [bool] Is eval result higher better, e.g. AUC is is_higher_better.

For multi-class task, the y_pred is group by class_id first, then group by row_id. If you want to get i-th row y_pred in j-th class, the access way is `y_pred[j * num_data + i]`.

get_params (*deep=True*)

Get parameters for this estimator.

Parameters **deep** (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns **params** – Parameter names mapped to their values.

Return type dict

n_classes_

Get the number of classes.

n_features_

Get the number of features of fitted model.

objective_

Get the concrete objective used while fitting this model.

predict (*X, raw_score=False, num_iteration=None, pred_leaf=False, pred_contrib=False, **kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*array-like or sparse matrix of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **num_iteration** (*int or None, optional (default=None)*) – Limit number of iterations in the prediction. If None, if the best iteration exists, it is used; otherwise, all trees are used. If ≤ 0 , all trees are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

Note: If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (<https://github.com>).

[com/slundberg/shap](https://github.com/slundberg/shap)). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (array-like of shape = $[n_samples]$ or shape = $[n_samples, n_classes]$) – The predicted values.
- **X_leaves** (array-like of shape = $[n_samples, n_trees]$ or shape = $[n_samples, n_trees * n_classes]$) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (array-like of shape = $[n_samples, n_features + 1]$ or shape = $[n_samples, (n_features + 1) * n_classes]$) – If `pred_contrib=True`, the feature contributions for each sample.

predict_proba (*X*, *raw_score=False*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, ****kwargs**)

Return the predicted probability for each class for each sample.

Parameters

- **X** (array-like or sparse matrix of shape = $[n_samples, n_features]$) – Input features matrix.
- **raw_score** (*bool*, optional (default=False)) – Whether to predict raw scores.
- **num_iteration** (*int* or *None*, optional (default=None)) – Limit number of iterations in the prediction. If *None*, if the best iteration exists, it is used; otherwise, all trees are used. If ≤ 0 , all trees are used (no limits).
- **pred_leaf** (*bool*, optional (default=False)) – Whether to predict leaf index.
- **pred_contrib** (*bool*, optional (default=False)) – Whether to predict feature contributions.

Note: If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (<https://github.com/slundberg/shap>). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_probability** (array-like of shape = $[n_samples, n_classes]$) – The predicted probability for each class for each sample.
- **X_leaves** (array-like of shape = $[n_samples, n_trees * n_classes]$) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (array-like of shape = $[n_samples, (n_features + 1) * n_classes]$) – If `pred_contrib=True`, the feature contributions for each sample.

set_params (****params**)

Set the parameters of this estimator.

Parameters ****params** – Parameter names with their new values.

Returns **self** – Returns self.

Return type object

9.3.3 lightgbm.LGBMRegressor

```
class lightgbm.LGBMRegressor(boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=-1, silent=True, importance_type='split', **kwargs)
```

Bases: lightgbm.sklearn.LGBMModel, object

LightGBM regressor.

```
__init__(boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=-1, silent=True, importance_type='split', **kwargs)
```

Construct a gradient boosting model.

Parameters

- **boosting_type** (*string, optional (default='gbdt')*) – 'gbdt', traditional Gradient Boosting Decision Tree. 'dart', Dropouts meet Multiple Additive Regression Trees. 'goss', Gradient-based One-Side Sampling. 'rf', Random Forest.
- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.
- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, <=0 means no limit.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use `callbacks` parameter of `fit` method to shrink/adapt learning rate in training using `reset_parameter` callback. Note, that this will ignore the `learning_rate` argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.
- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*string, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: 'regression' for LGBMRegressor, 'binary' or 'multiclass' for LGBMClassifier, 'lambda_rank' for LGBMRanker.
- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form {class_label: weight}. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these

parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (<https://scikit-learn.org/stable/modules/calibration.html>) of your model. The ‘balanced’ mode uses the values of `y` to automatically adjust weights inversely proportional to class frequencies in the input data as `n_samples / (n_classes * np.bincount(y))`. If `None`, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the `fit` method) if `sample_weight` is specified.

- **min_split_gain**(*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight**(*float, optional (default=1e-3)*) – Minimum sum of instance weight (hessian) needed in a child (leaf).
- **min_child_samples**(*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample**(*float, optional (default=1.)*) – Subsample ratio of the training instance.
- **subsample_freq**(*int, optional (default=0)*) – Frequency of subsample, `<=0` means no enable.
- **colsample_bytree**(*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha**(*float, optional (default=0.)*) – L1 regularization term on weights.
- **reg_lambda**(*float, optional (default=0.)*) – L2 regularization term on weights.
- **random_state**(*int or None, optional (default=None)*) – Random number seed. If `None`, default seeds in C++ code will be used.
- **n_jobs**(*int, optional (default=-1)*) – Number of parallel threads.
- **silent**(*bool, optional (default=True)*) – Whether to print messages while running boosting.
- **importance_type**(*string, optional (default='split')*) – The type of feature importance to be filled into `feature_importances_`. If ‘split’, result contains numbers of times the feature is used in a model. If ‘gain’, result contains total gains of splits which use the feature.
- ****kwargs** – Other parameters for the model. Check <http://lightgbm.readthedocs.io/en/latest/Parameters.html> for more parameters.

Warning: `**kwargs` is not supported in sklearn, it may cause unexpected issues.

n_features_

The number of features of fitted model.

Type int

classes_

The class label array (only for classification problem).

Type array of shape = [n_classes]

n_classes_
The number of classes (only for classification problem).
Type int

best_score_
The best score of fitted model.
Type dict or None

best_iteration_
The best iteration of fitted model if `early_stopping_rounds` has been specified.
Type int or None

objective_
The concrete objective used while fitting this model.
Type string or callable

booster_
The underlying Booster of this model.
Type *Booster*

evals_result_
The evaluation results if `early_stopping_rounds` has been specified.
Type dict or None

feature_importances_
The feature importances (the higher, the more important the feature).
Type array of shape = [n_features]

Note: A custom objective function can be provided for the `objective` parameter. In this case, it should have the signature `objective(y_true, y_pred) -> grad, hess` or `objective(y_true, y_pred, group) -> grad, hess`:

y_true [array-like of shape = [n_samples]] The target values.

y_pred [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values.

group [array-like] Group/query data, used for ranking task.

grad [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the first order derivative (gradient) for each sample point.

hess [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the second order derivative (Hessian) for each sample point.

For multi-class task, the `y_pred` is group by `class_id` first, then group by `row_id`. If you want to get `i`-th row `y_pred` in `j`-th class, the access way is `y_pred[j * num_data + i]` and you should group `grad` and `hess` in this way as well.

Methods

| | |
|--|--------------------------------------|
| <code>__init__</code> ([boosting_type, num_leaves, ...]) | Construct a gradient boosting model. |
|--|--------------------------------------|

Continued on next page

Table 10 – continued from previous page

| | |
|--|---|
| <code>fit(X, y[, sample_weight, init_score, ...])</code> | Build a gradient boosting model from the training set (X, y). |
| <code>get_params([deep])</code> | Get parameters for this estimator. |
| <code>predict(X[, raw_score, num_iteration, ...])</code> | Return the predicted value for each sample. |
| <code>set_params(**params)</code> | Set the parameters of this estimator. |

Attributes

| | |
|-----------------------------------|---|
| <code>best_iteration_</code> | Get the best iteration of fitted model. |
| <code>best_score_</code> | Get the best score of fitted model. |
| <code>booster_</code> | Get the underlying lightgbm Booster of this model. |
| <code>evals_result_</code> | Get the evaluation results. |
| <code>feature_importances_</code> | Get feature importances. |
| <code>n_features_</code> | Get the number of features of fitted model. |
| <code>objective_</code> | Get the concrete objective used while fitting this model. |

best_iteration_

Get the best iteration of fitted model.

best_score_

Get the best score of fitted model.

booster_

Get the underlying lightgbm Booster of this model.

evals_result_

Get the evaluation results.

feature_importances_

Get feature importances.

Note: Feature importance in sklearn interface used to normalize to 1, it's deprecated after 2.0.4 and is the same as `Booster.feature_importance()` now. `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

fit (X, y, sample_weight=None, init_score=None, eval_set=None, eval_names=None, eval_sample_weight=None, eval_init_score=None, eval_metric=None, early_stopping_rounds=None, verbose=True, feature_name='auto', categorical_feature='auto', callbacks=None)
Build a gradient boosting model from the training set (X, y).

Parameters

- **X** (array-like or sparse matrix of shape = [n_samples, n_features]) – Input feature matrix.
- **y** (array-like of shape = [n_samples]) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (array-like of shape = [n_samples] or None, optional (default=None)) – Weights of training data.
- **init_score** (array-like of shape = [n_samples] or None, optional (default=None)) – Init score of training data.

- **group** (*array-like or None, optional (default=None)*) – Group data of training data.
- **eval_set** (*list or None, optional (default=None)*) – A list of (X, y) tuple pairs to use as validation sets.
- **eval_names** (*list of strings or None, optional (default=None)*) – Names of eval_set.
- **eval_sample_weight** (*list of arrays or None, optional (default=None)*) – Weights of eval data.
- **eval_init_score** (*list of arrays or None, optional (default=None)*) – Init score of eval data.
- **eval_group** (*list of arrays or None, optional (default=None)*) – Group data of eval data.
- **eval_metric** (*string, list of strings, callable or None, optional (default=None)*) – If string, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. In either case, the metric from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.
- **early_stopping_rounds** (*int or None, optional (default=None)*) – Activates early stopping. The model will train until the validation score stops improving. Validation score needs to improve at least every early_stopping_rounds round(s) to continue training. Requires at least one validation data and one metric. If there's more than one, will check all of them. But the training data is ignored anyway. To check only the first metric, set the first_metric_only parameter to True in additional parameters **kwargs of the model constructor.
- **verbose** (*bool or int, optional (default=True)*) – Requires at least one evaluation data. If True, the eval metric on the eval set is printed at each boosting stage. If int, the eval metric on the eval set is printed at every verbose boosting stage. The last boosting stage or the boosting stage found by using early_stopping_rounds is also printed.

Example

With verbose = 4 and at least one item in eval_set, an evaluation metric is printed every 4 (instead of 1) boosting stages.

- **feature_name** (*list of strings or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of strings or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of strings, interpreted as feature names (need to specify feature_name as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature.

- **callbacks** (*list of callback functions or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.

Returns self – Returns self.

Return type object

Note: Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`, `func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns `(eval_name, eval_result, is_higher_better)` or list of `(eval_name, eval_result, is_higher_better)`:

y_true [array-like of shape = `[n_samples]`] The target values.

y_pred [array-like of shape = `[n_samples]` or shape = `[n_samples * n_classes]` (for multi-class task)] The predicted values.

weight [array-like of shape = `[n_samples]`] The weight of samples.

group [array-like] Group/query data, used for ranking task.

eval_name [string] The name of evaluation function (without whitespaces).

eval_result [float] The eval result.

is_higher_better [bool] Is eval result higher better, e.g. AUC is `is_higher_better`.

For multi-class task, the `y_pred` is group by `class_id` first, then group by `row_id`. If you want to get `i`-th row `y_pred` in `j`-th class, the access way is `y_pred[j * num_data + i]`.

get_params (*deep=True*)

Get parameters for this estimator.

Parameters **deep** (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns **params** – Parameter names mapped to their values.

Return type dict

n_features_

Get the number of features of fitted model.

objective_

Get the concrete objective used while fitting this model.

predict (*X, raw_score=False, num_iteration=None, pred_leaf=False, pred_contrib=False, **kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*array-like or sparse matrix of shape = `[n_samples, n_features]`*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **num_iteration** (*int or None, optional (default=None)*) – Limit number of iterations in the prediction. If None, if the best iteration exists, it is used; otherwise, all trees are used. If `<= 0`, all trees are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.

- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

Note: If you want to get more explanations for your model’s predictions using SHAP values, like SHAP interaction values, you can install the shap package (<https://github.com/slundberg/shap>). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (*array-like of shape = [n_samples] or shape = [n_samples, n_classes]*) – The predicted values.
- **X_leaves** (*array-like of shape = [n_samples, n_trees] or shape = [n_samples, n_trees * n_classes]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*array-like of shape = [n_samples, n_features + 1] or shape = [n_samples, (n_features + 1) * n_classes]*) – If `pred_contrib=True`, the feature contributions for each sample.

set_params (***params*)

Set the parameters of this estimator.

Parameters ****params** – Parameter names with their new values.

Returns **self** – Returns self.

Return type object

9.3.4 lightgbm.LGBMRanker

class lightgbm.LGBMRanker (*boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=-1, silent=True, importance_type='split', **kwargs*)

Bases: lightgbm.sklearn.LGBMModel

LightGBM ranker.

__init__ (*boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=-1, silent=True, importance_type='split', **kwargs*)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*string, optional (default='gbdt')*) – ‘gbdt’, traditional Gradient Boosting Decision Tree. ‘dart’, Dropouts meet Multiple Additive Regression Trees. ‘goss’, Gradient-based One-Side Sampling. ‘rf’, Random Forest.

- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.
- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, ≤ 0 means no limit.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use `callbacks` parameter of `fit` method to shrink/adapt learning rate in training using `reset_parameter` callback. Note, that this will ignore the `learning_rate` argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.
- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*string, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: ‘regression’ for LGBMRegressor, ‘binary’ or ‘multiclass’ for LGBMClassifier, ‘lambdarank’ for LGBMRanker.
- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form `{class_label: weight}`. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (<https://scikit-learn.org/stable/modules/calibration.html>) of your model. The ‘balanced’ mode uses the values of `y` to automatically adjust weights inversely proportional to class frequencies in the input data as `n_samples / (n_classes * np.bincount(y))`. If `None`, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the `fit` method) if `sample_weight` is specified.
- **min_split_gain** (*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight** (*float, optional (default=1e-3)*) – Minimum sum of instance weight (hessian) needed in a child (leaf).
- **min_child_samples** (*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample** (*float, optional (default=1.)*) – Subsample ratio of the training instance.
- **subsample_freq** (*int, optional (default=0)*) – Frequency of subsample, ≤ 0 means no enable.
- **colsample_bytree** (*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha** (*float, optional (default=0.)*) – L1 regularization term on weights.
- **reg_lambda** (*float, optional (default=0.)*) – L2 regularization term on weights.

- **random_state** (*int or None, optional (default=None)*) – Random number seed. If None, default seeds in C++ code will be used.
- **n_jobs** (*int, optional (default=-1)*) – Number of parallel threads.
- **silent** (*bool, optional (default=True)*) – Whether to print messages while running boosting.
- **importance_type** (*string, optional (default='split')*) – The type of feature importance to be filled into `feature_importances_`. If 'split', result contains numbers of times the feature is used in a model. If 'gain', result contains total gains of splits which use the feature.
- ****kwargs** – Other parameters for the model. Check <http://lightgbm.readthedocs.io/en/latest/Parameters.html> for more parameters.

Warning: `**kwargs` is not supported in sklearn, it may cause unexpected issues.

n_features_

The number of features of fitted model.

Type int

classes_

The class label array (only for classification problem).

Type array of shape = [n_classes]

n_classes_

The number of classes (only for classification problem).

Type int

best_score_

The best score of fitted model.

Type dict or None

best_iteration_

The best iteration of fitted model if `early_stopping_rounds` has been specified.

Type int or None

objective_

The concrete objective used while fitting this model.

Type string or callable

booster_

The underlying Booster of this model.

Type *Booster*

evals_result_

The evaluation results if `early_stopping_rounds` has been specified.

Type dict or None

feature_importances_

The feature importances (the higher, the more important the feature).

Type array of shape = [n_features]

Note: A custom objective function can be provided for the `objective` parameter. In this case, it should have the signature `objective(y_true, y_pred) -> grad, hess` or `objective(y_true, y_pred, group) -> grad, hess`:

y_true [array-like of shape = [n_samples]] The target values.

y_pred [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values.

group [array-like] Group/query data, used for ranking task.

grad [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the first order derivative (gradient) for each sample point.

hess [array-like of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the second order derivative (Hessian) for each sample point.

For multi-class task, the `y_pred` is group by `class_id` first, then group by `row_id`. If you want to get `i`-th row `y_pred` in `j`-th class, the access way is `y_pred[j * num_data + i]` and you should group `grad` and `hess` in this way as well.

Methods

| | |
|--|---|
| <code>__init__([boosting_type, num_leaves, ...])</code> | Construct a gradient boosting model. |
| <code>fit(X, y[, sample_weight, init_score, ...])</code> | Build a gradient boosting model from the training set (X, y). |
| <code>get_params([deep])</code> | Get parameters for this estimator. |
| <code>predict(X[, raw_score, num_iteration, ...])</code> | Return the predicted value for each sample. |
| <code>set_params(**params)</code> | Set the parameters of this estimator. |

Attributes

| | |
|-----------------------------------|---|
| <code>best_iteration_</code> | Get the best iteration of fitted model. |
| <code>best_score_</code> | Get the best score of fitted model. |
| <code>booster_</code> | Get the underlying lightgbm Booster of this model. |
| <code>evals_result_</code> | Get the evaluation results. |
| <code>feature_importances_</code> | Get feature importances. |
| <code>n_features_</code> | Get the number of features of fitted model. |
| <code>objective_</code> | Get the concrete objective used while fitting this model. |

best_iteration_
Get the best iteration of fitted model.

best_score_
Get the best score of fitted model.

booster_
Get the underlying lightgbm Booster of this model.

evals_result_
Get the evaluation results.

feature_importances_

Get feature importances.

Note: Feature importance in sklearn interface used to normalize to 1, it's deprecated after 2.0.4 and is the same as `Booster.feature_importance()` now. `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

fit (*X*, *y*, *sample_weight*=None, *init_score*=None, *group*=None, *eval_set*=None, *eval_names*=None, *eval_sample_weight*=None, *eval_init_score*=None, *eval_group*=None, *eval_metric*=None, *eval_at*=[1], *early_stopping_rounds*=None, *verbose*=True, *feature_name*='auto', *categorical_feature*='auto', *callbacks*=None)
 Build a gradient boosting model from the training set (*X*, *y*).

Parameters

- **X** (array-like or sparse matrix of shape = [*n_samples*, *n_features*]) – Input feature matrix.
- **y** (array-like of shape = [*n_samples*]) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (array-like of shape = [*n_samples*] or None, optional (default=None)) – Weights of training data.
- **init_score** (array-like of shape = [*n_samples*] or None, optional (default=None)) – Init score of training data.
- **group** (array-like or None, optional (default=None)) – Group data of training data.
- **eval_set** (list or None, optional (default=None)) – A list of (*X*, *y*) tuple pairs to use as validation sets.
- **eval_names** (list of strings or None, optional (default=None)) – Names of eval_set.
- **eval_sample_weight** (list of arrays or None, optional (default=None)) – Weights of eval data.
- **eval_init_score** (list of arrays or None, optional (default=None)) – Init score of eval data.
- **eval_group** (list of arrays or None, optional (default=None)) – Group data of eval data.
- **eval_metric** (string, list of strings, callable or None, optional (default=None)) – If string, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. In either case, the `metric` from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.
- **eval_at** (list of int, optional (default=[1])) – The evaluation positions of the specified metric.
- **early_stopping_rounds** (int or None, optional (default=None)) – Activates early stopping. The model will train until the validation score stops improving. Validation score needs to improve at least every `early_stopping_rounds` round(s) to continue training. Requires at least one validation data and one metric. If there's more than one, will check all of them. But the training data is ignored anyway. To check only the first metric, set the

`first_metric_only` parameter to `True` in additional parameters `**kwargs` of the model constructor.

- **verbose** (*bool or int, optional (default=True)*) – Requires at least one evaluation data. If `True`, the eval metric on the eval set is printed at each boosting stage. If `int`, the eval metric on the eval set is printed at every `verbose` boosting stage. The last boosting stage or the boosting stage found by using `early_stopping_rounds` is also printed.

Example

With `verbose = 4` and at least one item in `eval_set`, an evaluation metric is printed every 4 (instead of 1) boosting stages.

- **feature_name** (*list of strings or 'auto', optional (default='auto')*) – Feature names. If `'auto'` and data is pandas `DataFrame`, data columns names are used.
- **categorical_feature** (*list of strings or int, or 'auto', optional (default='auto')*) – Categorical features. If list of `int`, interpreted as indices. If list of strings, interpreted as feature names (need to specify `feature_name` as well). If `'auto'` and data is pandas `DataFrame`, pandas unordered categorical columns are used. All values in categorical features should be less than `int32` max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature.
- **callbacks** (*list of callback functions or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.

Returns `self` – Returns self.

Return type `object`

Note: Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`, `func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns `(eval_name, eval_result, is_higher_better)` or list of `(eval_name, eval_result, is_higher_better)`:

y_true [array-like of shape = `[n_samples]`] The target values.

y_pred [array-like of shape = `[n_samples]` or shape = `[n_samples * n_classes]` (for multi-class task)] The predicted values.

weight [array-like of shape = `[n_samples]`] The weight of samples.

group [array-like] Group/query data, used for ranking task.

eval_name [string] The name of evaluation function (without whitespaces).

eval_result [float] The eval result.

is_higher_better [bool] Is eval result higher better, e.g. AUC is `is_higher_better`.

For multi-class task, the `y_pred` is group by `class_id` first, then group by `row_id`. If you want to get `i`-th row `y_pred` in `j`-th class, the access way is `y_pred[j * num_data + i]`.

get_params (*deep=True*)

Get parameters for this estimator.

Parameters *deep* (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns *params* – Parameter names mapped to their values.

Return type dict

n_features_

Get the number of features of fitted model.

objective_

Get the concrete objective used while fitting this model.

predict (*X*, *raw_score=False*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, ***kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*array-like or sparse matrix of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **num_iteration** (*int or None, optional (default=None)*) – Limit number of iterations in the prediction. If None, if the best iteration exists, it is used; otherwise, all trees are used. If ≤ 0 , all trees are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

Note: If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (<https://github.com/slundberg/shap>). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (*array-like of shape = [n_samples] or shape = [n_samples, n_classes]*) – The predicted values.
- **X_leaves** (*array-like of shape = [n_samples, n_trees] or shape = [n_samples, n_trees * n_classes]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*array-like of shape = [n_samples, n_features + 1] or shape = [n_samples, (n_features + 1) * n_classes]*) – If `pred_contrib=True`, the feature contributions for each sample.

set_params (***params*)

Set the parameters of this estimator.

Parameters ***params* – Parameter names with their new values.

Returns `self` – Returns self.

Return type `object`

9.4 Callbacks

| | |
|--|---|
| <code>early_stopping(stopping_rounds[,...])</code> | Create a callback that activates early stopping. |
| <code>print_evaluation([period, show_stdv])</code> | Create a callback that prints the evaluation results. |
| <code>record_evaluation(eval_result)</code> | Create a callback that records the evaluation history into <code>eval_result</code> . |
| <code>reset_parameter(**kwargs)</code> | Create a callback that resets the parameter after the first iteration. |

9.4.1 `lightgbm.early_stopping`

`lightgbm.early_stopping(stopping_rounds, first_metric_only=False, verbose=True)`

Create a callback that activates early stopping.

Activates early stopping. The model will train until the validation score stops improving. Validation score needs to improve at least every `early_stopping_rounds` round(s) to continue training. Requires at least one validation data and one metric. If there's more than one, will check all of them. But the training data is ignored anyway. To check only the first metric set `first_metric_only` to `True`.

Parameters

- **`stopping_rounds`** (*int*) – The possible number of rounds without the trend occurrence.
- **`first_metric_only`** (*bool, optional (default=False)*) – Whether to use only the first metric for early stopping.
- **`verbose`** (*bool, optional (default=True)*) – Whether to print message with early stopping information.

Returns `callback` – The callback that activates early stopping.

Return type `function`

9.4.2 `lightgbm.print_evaluation`

`lightgbm.print_evaluation(period=1, show_stdv=True)`

Create a callback that prints the evaluation results.

Parameters

- **`period`** (*int, optional (default=1)*) – The period to print the evaluation results.
- **`show_stdv`** (*bool, optional (default=True)*) – Whether to show stdv (if provided).

Returns `callback` – The callback that prints the evaluation results every `period` iteration(s).

Return type `function`

9.4.3 lightgbm.record_evaluation

`lightgbm.record_evaluation(eval_result)`

Create a callback that records the evaluation history into `eval_result`.

Parameters `eval_result` (*dict*) – A dictionary to store the evaluation results.

Returns `callback` – The callback that records the evaluation history into the passed dictionary.

Return type function

9.4.4 lightgbm.reset_parameter

`lightgbm.reset_parameter(**kwargs)`

Create a callback that resets the parameter after the first iteration.

Note: The initial parameter will still take in-effect on first iteration.

Parameters `**kwargs` (*value should be list or function*) – List of parameters for each boosting round or a customized function that calculates the parameter in terms of current number of round (e.g. yields learning rate decay). If list `lst`, `parameter = lst[current_round]`. If function `func`, `parameter = func(current_round)`.

Returns `callback` – The callback that resets the parameter after the first iteration.

Return type function

9.5 Plotting

| | |
|--|--|
| <code>plot_importance(booster[, ax, height, xlim, ...])</code> | Plot model's feature importances. |
| <code>plot_split_value_histogram(booster, feature)</code> | Plot split value histogram for the specified feature of the model. |
| <code>plot_metric(booster[, metric, ...])</code> | Plot one metric during training. |
| <code>plot_tree(booster[, ax, tree_index, ...])</code> | Plot specified tree. |
| <code>create_tree_digraph(booster[, tree_index, ...])</code> | Create a digraph representation of specified tree. |

9.5.1 lightgbm.plot_importance

`lightgbm.plot_importance(booster, ax=None, height=0.2, xlim=None, ylim=None, title='Feature importance', xlabel='Feature importance', ylabel='Features', importance_type='split', max_num_features=None, ignore_zero=True, figsize=None, dpi=None, grid=True, precision=3, **kwargs)`

Plot model's feature importances.

Parameters

- **booster** (*Booster or LGBMModel*) – Booster or LGBMModel instance which feature importance should be plotted.
- **ax** (*matplotlib.axes.Axes or None, optional (default=None)*) – Target axes instance. If None, new figure and axes will be created.
- **height** (*float, optional (default=0.2)*) – Bar height, passed to `ax`.

- `barh()`.
- **xlim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.xlim()`.
 - **ylim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.ylim()`.
 - **title** (*string or None, optional (default="Feature importance")*) – Axes title. If None, title is disabled.
 - **xlabel** (*string or None, optional (default="Feature importance")*) – X-axis title label. If None, title is disabled.
 - **ylabel** (*string or None, optional (default="Features")*) – Y-axis title label. If None, title is disabled.
 - **importance_type** (*string, optional (default="split")*) – How the importance is calculated. If “split”, result contains numbers of times the feature is used in a model. If “gain”, result contains total gains of splits which use the feature.
 - **max_num_features** (*int or None, optional (default=None)*) – Max number of top features displayed on plot. If None or <1, all features will be displayed.
 - **ignore_zero** (*bool, optional (default=True)*) – Whether to ignore features with zero importance.
 - **figsize** (*tuple of 2 elements or None, optional (default=None)*) – Figure size.
 - **dpi** (*int or None, optional (default=None)*) – Resolution of the figure.
 - **grid** (*bool, optional (default=True)*) – Whether to add a grid for axes.
 - **precision** (*int or None, optional (default=3)*) – Used to restrict the display of floating point values to a certain precision.
 - ****kwargs** – Other parameters passed to `ax.barh()`.

Returns `ax` – The plot with model’s feature importances.

Return type `matplotlib.axes.Axes`

9.5.2 `lightgbm.plot_split_value_histogram`

`lightgbm.plot_split_value_histogram` (*booster, feature, bins=None, ax=None, width_coef=0.8, xlim=None, ylim=None, title='Split value histogram for feature with @index/name@ @feature@', xlabel='Feature split value', ylabel='Count', figsize=None, dpi=None, grid=True, **kwargs*)

Plot split value histogram for the specified feature of the model.

Parameters

- **booster** (*Booster or LGBMModel*) – Booster or LGBMModel instance of which feature split value histogram should be plotted.
- **feature** (*int or string*) – The feature name or index the histogram is plotted for. If int, interpreted as index. If string, interpreted as name.
- **bins** (*int, string or None, optional (default=None)*) – The maximum number of bins. If None, the number of bins equals number of unique split values. If

string, it should be one from the list of the supported values by `numpy.histogram()` function.

- **ax** (*matplotlib.axes.Axes or None, optional (default=None)*) – Target axes instance. If None, new figure and axes will be created.
- **width_coef** (*float, optional (default=0.8)*) – Coefficient for histogram bar width.
- **xlim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.xlim()`.
- **ylim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.ylim()`.
- **title** (*string or None, optional (default="Split value histogram for feature with @index/name@ @feature@")*) – Axes title. If None, title is disabled. `@feature@` placeholder can be used, and it will be replaced with the value of feature parameter. `@index/name@` placeholder can be used, and it will be replaced with index word in case of int type feature parameter or name word in case of string type feature parameter.
- **xlabel** (*string or None, optional (default="Feature split value")*) – X-axis title label. If None, title is disabled.
- **ylabel** (*string or None, optional (default="Count")*) – Y-axis title label. If None, title is disabled.
- **figsize** (*tuple of 2 elements or None, optional (default=None)*) – Figure size.
- **dpi** (*int or None, optional (default=None)*) – Resolution of the figure.
- **grid** (*bool, optional (default=True)*) – Whether to add a grid for axes.
- ****kwargs** – Other parameters passed to `ax.bar()`.

Returns **ax** – The plot with specified model's feature split value histogram.

Return type `matplotlib.axes.Axes`

9.5.3 lightgbm.plot_metric

`lightgbm.plot_metric(booster, metric=None, dataset_names=None, ax=None, xlim=None, ylim=None, title='Metric during training', xlabel='Iterations', ylabel='auto', figsize=None, dpi=None, grid=True)`

Plot one metric during training.

Parameters

- **booster** (*dict or LGBMModel*) – Dictionary returned from `lightgbm.train()` or `LGBMModel` instance.
- **metric** (*string or None, optional (default=None)*) – The metric name to plot. Only one metric supported because different metrics have various scales. If None, first metric picked from dictionary (according to hashcode).
- **dataset_names** (*list of strings or None, optional (default=None)*) – List of the dataset names which are used to calculate metric to plot. If None, all datasets are used.

- **ax** (*matplotlib.axes.Axes or None, optional (default=None)*) – Target axes instance. If None, new figure and axes will be created.
- **xlim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.xlim()`.
- **ylim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.ylim()`.
- **title** (*string or None, optional (default="Metric during training")*) – Axes title. If None, title is disabled.
- **xlabel** (*string or None, optional (default="Iterations")*) – X-axis title label. If None, title is disabled.
- **ylabel** (*string or None, optional (default="auto")*) – Y-axis title label. If 'auto', metric name is used. If None, title is disabled.
- **figsize** (*tuple of 2 elements or None, optional (default=None)*) – Figure size.
- **dpi** (*int or None, optional (default=None)*) – Resolution of the figure.
- **grid** (*bool, optional (default=True)*) – Whether to add a grid for axes.

Returns **ax** – The plot with metric's history over the training.

Return type `matplotlib.axes.Axes`

9.5.4 `lightgbm.plot_tree`

`lightgbm.plot_tree` (*booster, ax=None, tree_index=0, figsize=None, dpi=None, old_graph_attr=None, old_node_attr=None, old_edge_attr=None, show_info=None, precision=3, **kwargs*)

Plot specified tree.

Note: It is preferable to use `create_tree_digraph()` because of its lossless quality and returned objects can be also rendered and displayed directly inside a Jupyter notebook.

Parameters

- **booster** (*Booster or LGBMModel*) – Booster or LGBMModel instance to be plotted.
- **ax** (*matplotlib.axes.Axes or None, optional (default=None)*) – Target axes instance. If None, new figure and axes will be created.
- **tree_index** (*int, optional (default=0)*) – The index of a target tree to plot.
- **figsize** (*tuple of 2 elements or None, optional (default=None)*) – Figure size.
- **dpi** (*int or None, optional (default=None)*) – Resolution of the figure.
- **show_info** (*list of strings or None, optional (default=None)*) – What information should be shown in nodes. Possible values of list items: 'split_gain', 'internal_value', 'internal_count', 'internal_weight', 'leaf_count', 'leaf_weight', 'data_percentage'.

- **precision** (*int or None, optional (default=3)*) – Used to restrict the display of floating point values to a certain precision.
- ****kwargs** – Other parameters passed to `Digraph` constructor. Check <https://graphviz.readthedocs.io/en/stable/api.html#digraph> for the full list of supported parameters.

Returns `ax` – The plot with single tree.

Return type `matplotlib.axes.Axes`

9.5.5 `lightgbm.create_tree_digraph`

```
lightgbm.create_tree_digraph(booster, tree_index=0, show_info=None, precision=3,
                             old_name=None, old_comment=None, old_filename=None,
                             old_directory=None, old_format=None, old_engine=None,
                             old_encoding=None, old_graph_attr=None, old_node_attr=None,
                             old_edge_attr=None, old_body=None, old_strict=False,
                             **kwargs)
```

Create a digraph representation of specified tree.

Note: For more information please visit <https://graphviz.readthedocs.io/en/stable/api.html#digraph>.

Parameters

- **booster** (`Booster` or `LGBMModel`) – `Booster` or `LGBMModel` instance to be converted.
- **tree_index** (*int, optional (default=0)*) – The index of a target tree to convert.
- **show_info** (*list of strings or None, optional (default=None)*) – What information should be shown in nodes. Possible values of list items: ‘split_gain’, ‘internal_value’, ‘internal_count’, ‘internal_weight’, ‘leaf_count’, ‘leaf_weight’, ‘data_percentage’.
- **precision** (*int or None, optional (default=3)*) – Used to restrict the display of floating point values to a certain precision.
- ****kwargs** – Other parameters passed to `Digraph` constructor. Check <https://graphviz.readthedocs.io/en/stable/api.html#digraph> for the full list of supported parameters.

Returns `graph` – The digraph representation of specified tree.

Return type `graphviz.Digraph`

Parallel Learning Guide

This is a guide for parallel learning of LightGBM.

Follow the [Quick Start](#) to know how to use LightGBM first.

10.1 Choose Appropriate Parallel Algorithm

LightGBM provides 3 parallel learning algorithms now.

| Parallel Algorithm | How to Use |
|--------------------|-----------------------------------|
| Data parallel | <code>tree_learner=data</code> |
| Feature parallel | <code>tree_learner=feature</code> |
| Voting parallel | <code>tree_learner=voting</code> |

These algorithms are suited for different scenarios, which is listed in the following table:

| | #data is small | #data is large |
|-------------------|------------------|-----------------|
| #feature is small | Feature Parallel | Data Parallel |
| #feature is large | Feature Parallel | Voting Parallel |

More details about these parallel algorithms can be found in [optimization in parallel learning](#).

10.2 Build Parallel Version

Default build version support parallel learning based on the socket.

If you need to build parallel version with MPI support, please refer to [Installation Guide](#).

10.3 Preparation

10.3.1 Socket Version

It needs to collect IP of all machines that want to run parallel learning in and allocate one TCP port (assume 12345 here) for all machines, and change firewall rules to allow income of this port (12345). Then write these IP and ports in one file (assume `mlist.txt`), like following:

```
machine1_ip 12345
machine2_ip 12345
```

10.3.2 MPI Version

It needs to collect IP (or hostname) of all machines that want to run parallel learning in. Then write these IP in one file (assume `mlist.txt`) like following:

```
machine1_ip
machine2_ip
```

Note: For Windows users, need to start “smpd” to start MPI service. More details can be found [here](#).

10.4 Run Parallel Learning

10.4.1 Socket Version

1. Edit following parameters in config file:

`tree_learner=your_parallel_algorithm`, edit `your_parallel_algorithm` (e.g. `feature/data`) here.

`num_machines=your_num_machines`, edit `your_num_machines` (e.g. 4) here.

`machine_list_file=mlist.txt`, `mlist.txt` is created in *Preparation section*.

`local_listen_port=12345`, 12345 is allocated in *Preparation section*.

2. Copy data file, executable file, config file and `mlist.txt` to all machines.
3. Run following command on all machines, you need to change `your_config_file` to real config file.

For Windows: `lightgbm.exe config=your_config_file`

For Linux: `./lightgbm config=your_config_file`

10.4.2 MPI Version

1. Edit following parameters in config file:

`tree_learner=your_parallel_algorithm`, edit `your_parallel_algorithm` (e.g. `feature/data`) here.

`num_machines=your_num_machines`, edit `your_num_machines` (e.g. 4) here.

2. Copy data file, executable file, config file and `mlist.txt` to all machines.

Note: MPI needs to be run in the **same path on all machines**.

3. Run following command on one machine (not need to run on all machines), need to change `your_config_file` to real config file.

For Windows:

```
mpiexec.exe /machinefile mlist.txt lightgbm.exe config=your_config_file
```

For Linux:

```
mpiexec --machinefile mlist.txt ./lightgbm config=your_config_file
```

10.4.3 Example

- A simple parallel example

CHAPTER 11

LightGBM GPU Tutorial

The purpose of this document is to give you a quick step-by-step tutorial on GPU training.

For Windows, please see [GPU Windows Tutorial](#).

We will use the GPU instance on [Microsoft Azure cloud computing platform](#) for demonstration, but you can use any machine with modern AMD or NVIDIA GPUs.

11.1 GPU Setup

You need to launch a NV type instance on Azure (available in East US, North Central US, South Central US, West Europe and Southeast Asia zones) and select Ubuntu 16.04 LTS as the operating system.

For testing, the smallest NV6 type virtual machine is sufficient, which includes 1/2 M60 GPU, with 8 GB memory, 180 GB/s memory bandwidth and 4,825 GFLOPS peak computation power. Don't use the NC type instance as the GPUs (K80) are based on an older architecture (Kepler).

First we need to install minimal NVIDIA drivers and OpenCL development environment:

```
sudo apt-get update
sudo apt-get install --no-install-recommends nvidia-375
sudo apt-get install --no-install-recommends nvidia-opengl-icd-375 nvidia-opengl-dev
↪ opengl-headers
```

After installing the drivers you need to restart the server.

```
sudo init 6
```

After about 30 seconds, the server should be up again.

If you are using an AMD GPU, you should download and install the [AMDGPU-Pro](#) driver and also install package `ocl-icd-libopencl1` and `ocl-icd-opencl-dev`.

11.2 Build LightGBM

Now install necessary building tools and dependencies:

```
sudo apt-get install --no-install-recommends git cmake build-essential libboost-dev_  
↳libboost-system-dev libboost-filesystem-dev
```

The NV6 GPU instance has a 320 GB ultra-fast SSD mounted at /mnt. Let's use it as our workspace (skip this if you are using your own machine):

```
sudo mkdir -p /mnt/workspace  
sudo chown $(whoami):$(whoami) /mnt/workspace  
cd /mnt/workspace
```

Now we are ready to checkout LightGBM and compile it with GPU support:

```
git clone --recursive https://github.com/microsoft/LightGBM  
cd LightGBM  
mkdir build ; cd build  
cmake -DUSE_GPU=1 ..  
# if you have installed NVIDIA CUDA to a customized location, you should specify_  
↳paths to OpenCL headers and library like the following:  
# cmake -DUSE_GPU=1 -DOpenCL_LIBRARY=/usr/local/cuda/lib64/libOpenCL.so -DOpenCL_  
↳INCLUDE_DIR=/usr/local/cuda/include/ ..  
make -j$(nproc)  
cd ..
```

You will see two binaries are generated, `lightgbm` and `lib_lightgbm.so`.

If you are building on macOS, you probably need to remove macro `BOOST_COMPUTE_USE_OFFLINE_CACHE` in `src/treelerner/gpu_tree_learner.h` to avoid a known crash bug in `Boost.Compute`.

11.3 Install Python Interface (optional)

If you want to use the Python interface of LightGBM, you can install it now (along with some necessary Python-package dependencies):

```
sudo apt-get -y install python-pip  
sudo -H pip install setuptools numpy scipy scikit-learn -U  
cd python-package/  
sudo python setup.py install --precompile  
cd ..
```

You need to set an additional parameter `"device" : "gpu"` (along with your other options like `learning_rate`, `num_leaves`, etc) to use GPU in Python.

You can read our [Python-package Examples](#) for more information on how to use the Python interface.

11.4 Dataset Preparation

Using the following commands to prepare the Higgs dataset:

```
git clone https://github.com/guolinke/boosting_tree_benchmarks.git
cd boosting_tree_benchmarks/data
wget "https://archive.ics.uci.edu/ml/machine-learning-databases/00280/HIGGS.csv.gz"
gunzip HIGGS.csv.gz
python higgs2libsvm.py
cd ../../
ln -s boosting_tree_benchmarks/data/higgs.train
ln -s boosting_tree_benchmarks/data/higgs.test
```

Now we create a configuration file for LightGBM by running the following commands (please copy the entire block and run it as a whole):

```
cat > lightgbm_gpu.conf <<EOF
max_bin = 63
num_leaves = 255
num_iterations = 50
learning_rate = 0.1
tree_learner = serial
task = train
is_training_metric = false
min_data_in_leaf = 1
min_sum_hessian_in_leaf = 100
ndcg_eval_at = 1,3,5,10
sparse_threshold = 1.0
device = gpu
gpu_platform_id = 0
gpu_device_id = 0
EOF
echo "num_threads=$(nproc)" >> lightgbm_gpu.conf
```

GPU is enabled in the configuration file we just created by setting `device=gpu`. In this configuration we use the first GPU installed on the system (`gpu_platform_id=0` and `gpu_device_id=0`). If `gpu_platform_id` or `gpu_device_id` is not set, the default platform and GPU will be selected. You might have multiple platforms (AMD/Intel/NVIDIA) or GPUs. You can use the `clinfo` utility to identify the GPUs on each platform. On Ubuntu, you can install `clinfo` by executing `sudo apt-get install clinfo`. If you have a discrete GPU by AMD/NVIDIA and an integrated GPU by Intel, make sure to select the correct `gpu_platform_id` to use the discrete GPU.

11.5 Run Your First Learning Task on GPU

Now we are ready to start GPU training!

First we want to verify the GPU works correctly. Run the following command to train on GPU, and take a note of the AUC after 50 iterations:

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train valid=higgs.test_
↪objective=binary metric=auc
```

Now train the same dataset on CPU using the following command. You should observe a similar AUC:

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train valid=higgs.test_
↪objective=binary metric=auc device=cpu
```

Now we can make a speed test on GPU without calculating AUC after each iteration.

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train objective=binary metric=auc
```

Speed test on CPU:

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train objective=binary metric=auc_
↪device=cpu
```

You should observe over three times speedup on this GPU.

The GPU acceleration can be used on other tasks/metrics (regression, multi-class classification, ranking, etc) as well. For example, we can train the Higgs dataset on GPU as a regression task:

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train objective=regression_l2 metric=l2
```

Also, you can compare the training speed with CPU:

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train objective=regression_l2_
↪metric=l2 device=cpu
```

11.6 Further Reading

- [GPU Tuning Guide and Performance Comparison](#)
- [GPU SDK Correspondence and Device Targeting Table](#)
- [GPU Windows Tutorial](#)

11.7 Reference

Please kindly cite the following article in your publications if you find the GPU acceleration useful:

Huan Zhang, Si Si and Cho-Jui Hsieh. “[GPU Acceleration for Large-scale Tree Boosting.](#)” SysML Conference, 2018.

12.1 Missing Value Handle

- LightGBM enables the missing value handle by default. Disable it by setting `use_missing=false`.
- LightGBM uses NA (NaN) to represent missing values by default. Change it to use zero by setting `zero_as_missing=true`.
- When `zero_as_missing=false` (default), the unshown values in sparse matrices (and LightSVM) are treated as zeros.
- When `zero_as_missing=true`, NA and zeros (including unshown values in sparse matrices (and LightSVM)) are treated as missing.

12.2 Categorical Feature Support

- LightGBM offers good accuracy with integer-encoded categorical features. LightGBM applies [Fisher \(1958\)](#) to find the optimal split over categories as [described here](#). This often performs better than one-hot encoding.
- Use `categorical_feature` to specify the categorical features. Refer to the parameter `categorical_feature` in [Parameters](#).
- Categorical features must be encoded as non-negative integers (`int`) less than `Int32.MaxValue` (2147483647). It is best to use a contiguous range of integers started from zero.
- Use `min_data_per_group`, `cat_smooth` to deal with over-fitting (when `#data` is small or `#category` is large).
- For a categorical feature with high cardinality (`#category` is large), it often works best to treat the feature as numeric, either by simply ignoring the categorical interpretation of the integers or by embedding the categories in a low-dimensional numeric space.

12.3 LambdaRank

- The label should be of type `int`, such that larger numbers correspond to higher relevance (e.g. 0:bad, 1:fair, 2:good, 3:perfect).
- Use `label_gain` to set the gain(weight) of `int` label.
- Use `max_position` to set the NDCG optimization position.

12.4 Cost Efficient Gradient Boosting

Cost Efficient Gradient Boosting (CEGB) makes it possible to penalise boosting based on the cost of obtaining feature values. CEGB penalises learning in the following ways:

- Each time a tree is split, a penalty of `cegb_penalty_split` is applied.
- When a feature is used for the first time, `cegb_penalty_feature_coupled` is applied. This penalty can be different for each feature and should be specified as one `double` per feature.
- When a feature is used for the first time for a data row, `cegb_penalty_feature_lazy` is applied. Like `cegb_penalty_feature_coupled`, this penalty is specified as one `double` per feature.

Each of the penalties above is scaled by `cegb_tradeoff`. Using this parameter, it is possible to change the overall strength of the CEGB penalties by changing only one parameter.

12.5 Parameters Tuning

- Refer to [Parameters Tuning](#).

12.6 Parallel Learning

- Refer to [Parallel Learning Guide](#).

12.7 GPU Support

- Refer to [GPU Tutorial](#) and [GPU Targets](#).

12.8 Recommendations for gcc Users (MinGW, *nix)

- Refer to [gcc Tips](#).

LightGBM Frequently Asked Questions

- *Critical Issues*
- *General LightGBM Questions*
- *R-package*
- *Python-package*

13.1 Critical Issues

A **critical issue** could be a *crash*, *prediction error*, *nonsense output*, or something else requiring immediate attention.

Please post such an issue in the [Microsoft/LightGBM repository](#).

You may also ping a member of the core team according to the relevant area of expertise by mentioning them with the arabase (@) symbol:

- [@guolinke](#) **Guolin Ke** (C++ code / R-package / Python-package)
- [@chivee](#) **Qiwei Ye** (C++ code / Python-package)
- [@Laurae2](#) **Damien Soukhavong** (R-package)
- [@jameslamb](#) **James Lamb** (R-package)
- [@wxchan](#) **Wenxuan Chen** (Python-package)
- [@henry0312](#) **Tsukasa Omoto** (Python-package)
- [@StrikerRUS](#) **Nikita Titov** (Python-package)
- [@huanzhang12](#) **Huan Zhang** (GPU support)

Please include as much of the following information as possible when submitting a critical issue:

- Is it reproducible on CLI (command line interface), R, and/or Python?
- Is it specific to a wrapper? (R or Python?)
- Is it specific to the compiler? (gcc or Clang version? MinGW or Visual Studio version?)
- Is it specific to your Operating System? (Windows? Linux? macOS?)
- Are you able to reproduce this issue with a simple case?
- Does the issue persist after removing all optimization flags and compiling LightGBM in debug mode?

When submitting issues, please keep in mind that this is largely a volunteer effort, and we may not be available 24/7 to provide support.

13.2 General LightGBM Questions

- *1. Where do I find more details about LightGBM parameters?*
- *2. On datasets with millions of features, training does not start (or starts after a very long time).*
- *3. When running LightGBM on a large dataset, my computer runs out of RAM.*
- *4. I am using Windows. Should I use Visual Studio or MinGW for compiling LightGBM?*
- *5. When using LightGBM GPU, I cannot reproduce results over several runs.*
- *6. Bagging is not reproducible when changing the number of threads.*
- *7. I tried to use Random Forest mode, and LightGBM crashes!*
- *8. CPU usage is low (like 10%) in Windows when using LightGBM on very large datasets with many-core systems.*
- *9. When I'm trying to specify a categorical column with the `categorical_feature` parameter, I get the following sequence of warnings, but there are no negative values in the column.*
- *10. LightGBM crashes randomly with the error like: `Initializing libomp5.dylib, but found libomp.dylib already initialized.`*
- *11. LightGBM hangs when multithreading (OpenMP) and using forking in Linux at the same time.*
- *12. Why is early stopping not enabled by default in LightGBM?*
- *13. Does LightGBM support direct loading data from zero-based or one-based LibSVM format file?*

13.2.1 1. Where do I find more details about LightGBM parameters?

Take a look at [Parameters](#) and the [Laurae++/Parameters](#) website.

13.2.2 2. On datasets with millions of features, training does not start (or starts after a very long time).

Use a smaller value for `bin_construct_sample_cnt` and a larger value for `min_data`.

13.2.3 3. When running LightGBM on a large dataset, my computer runs out of RAM.

Multiple Solutions: set the `histogram_pool_size` parameter to the MB you want to use for LightGBM (`histogram_pool_size` + dataset size = approximately RAM used), lower `num_leaves` or lower `max_bin` (see [Microsoft/LightGBM#562](#)).

13.2.4 4. I am using Windows. Should I use Visual Studio or MinGW for compiling LightGBM?

Visual Studio performs best for LightGBM.

13.2.5 5. When using LightGBM GPU, I cannot reproduce results over several runs.

This is normal and expected behaviour, but you may try to use `gpu_use_dp = true` for reproducibility (see [Microsoft/LightGBM#560](#)). You may also use the CPU version.

13.2.6 6. Bagging is not reproducible when changing the number of threads.

LightGBM bagging is multithreaded, so its output depends on the number of threads used. There is [no workaround currently](#).

13.2.7 7. I tried to use Random Forest mode, and LightGBM crashes!

This is expected behaviour for arbitrary parameters. To enable Random Forest, you must use `bagging_fraction` and `feature_fraction` different from 1, along with a `bagging_freq`. [This thread](#) includes an example.

13.2.8 8. CPU usage is low (like 10%) in Windows when using LightGBM on very large datasets with many-core systems.

Please use Visual Studio as it may be 10x faster than MinGW especially for very large trees.

13.2.9 9. When I'm trying to specify a categorical column with the `categorical_feature` parameter, I get the following sequence of warnings, but there are no negative values in the column.

```
[LightGBM] [Warning] Met negative value in categorical features, will convert it to ↵
↵NaN
[LightGBM] [Warning] There are no meaningful features, as all feature values are ↵
↵constant.
```

The column you're trying to pass via `categorical_feature` likely contains very large values. Categorical features in LightGBM are limited by int32 range, so you cannot pass values that are greater than `Int32.MaxValue` (2147483647) as categorical features (see [Microsoft/LightGBM#1359](#)). You should convert them to integers ranging from zero to the number of categories first.

13.2.10 10. LightGBM crashes randomly with the error like: Initializing libiomp5.dylib, but found libomp.dylib already initialized.

```
OMP: Error #15: Initializing libiomp5.dylib, but found libomp.dylib already
↳ initialized.
OMP: Hint: This means that multiple copies of the OpenMP runtime have been linked
↳ into the program. That is dangerous, since it can degrade performance or cause
↳ incorrect results. The best thing to do is to ensure that only a single OpenMP
↳ runtime is linked into the process, e.g. by avoiding static linking of the OpenMP
↳ runtime in any library. As an unsafe, unsupported, undocumented workaround you can
↳ set the environment variable KMP_DUPLICATE_LIB_OK=TRUE to allow the program to
↳ continue to execute, but that may cause crashes or silently produce incorrect
↳ results. For more information, please see http://www.intel.com/software/products/
↳ support/.
```

Possible Cause: This error means that you have multiple OpenMP libraries installed on your machine and they conflict with each other. (File extensions in the error message may differ depending on the operating system).

If you are using Python distributed by Conda, then it is highly likely that the error is caused by the numpy package from Conda which includes the mkl package which in turn conflicts with the system-wide library. In this case you can update the numpy package in Conda or replace the Conda's OpenMP library instance with system-wide one by creating a symlink to it in Conda environment folder \$CONDA_PREFIX/lib.

Solution: Assuming you are using macOS with Homebrew, the command which overwrites OpenMP library files in the current active Conda environment with symlinks to the system-wide library ones installed by Homebrew:

```
ln -sf `ls -d "$(brew --cellar libomp)" */lib`/* $CONDA_PREFIX/lib
```

The described above fix worked fine before the release of OpenMP 8.0.0 version. Starting from 8.0.0 version, Homebrew formula for OpenMP includes `-DLIBOMP_INSTALL_ALIASES=OFF` option which leads to that the fix doesn't work anymore. However, you can create symlinks to library aliases manually:

```
for LIBOMP_ALIAS in libgomp.dylib libiomp5.dylib libomp.dylib; do sudo ln -sf "$(brew
↳ --cellar libomp)" */lib/libomp.dylib $CONDA_PREFIX/lib/$LIBOMP_ALIAS; done
```

Another workaround would be removing MKL optimizations from Conda's packages completely:

```
conda install nomkl
```

If this is not your case, then you should find conflicting OpenMP library installations on your own and leave only one of them.

13.2.11 11. LightGBM hangs when multithreading (OpenMP) and using forking in Linux at the same time.

Use `nthreads=1` to disable multithreading of LightGBM. There is a bug with OpenMP which hangs forked sessions with multithreading activated. A more expensive solution is to use new processes instead of using fork, however, keep in mind it is creating new processes where you have to copy memory and load libraries (example: if you want to fork 16 times your current process, then you will require to make 16 copies of your dataset in memory) (see [Microsoft/LightGBM#1789](#)).

An alternative, if multithreading is really necessary inside the forked sessions, would be to compile LightGBM with Intel toolchain. Intel compilers are unaffected by this bug.

For C/C++ users, any OpenMP feature cannot be used before the fork happens. If an OpenMP feature is used before the fork happens (example: using OpenMP for forking), OpenMP will hang inside the forked sessions. Use new processes instead and copy memory as required by creating new processes instead of forking (or, use Intel compilers).

13.2.12 12. Why is early stopping not enabled by default in LightGBM?

Early stopping involves choosing a validation set, a special type of holdout which is used to evaluate the current state of the model after each iteration to see if training can stop.

In LightGBM, we have decided to require that users specify this set directly. Many options exist for splitting training data into training, test, and validation sets.

The appropriate splitting strategy depends on the task and domain of the data, information that a modeler has but which LightGBM as a general-purpose tool does not.

13.2.13 13. Does LightGBM support direct loading data from zero-based or one-based LibSVM format file?

LightGBM supports loading data from zero-based LibSVM format file directly.

13.3 R-package

- 1. Any training command using LightGBM does not work after an error occurred during the training of a previous LightGBM model.
 - 2. I used `setinfo`, tried to print my `lgb.Dataset`, and now the R console froze!

13.3.1 1. Any training command using LightGBM does not work after an error occurred during the training of a previous LightGBM model.

Run `lgb.unloader(wipe = TRUE)` in the R console, and recreate the LightGBM datasets (this will wipe all LightGBM-related variables). Due to the pointers, choosing to not wipe variables will not fix the error. This is a known issue: [Microsoft/LightGBM#698](#).

13.3.2 2. I used `setinfo`, tried to print my `lgb.Dataset`, and now the R console froze!

Avoid printing the `lgb.Dataset` after using `setinfo`. This is a known bug: [Microsoft/LightGBM#539](#).

13.4 Python-package

- 1. *Error: setup script specifies an absolute path when installing from GitHub using python setup.py install.*
- 2. *Error messages: Cannot ... before construct dataset.*
- 3. *I encounter segmentation faults (segfaults) randomly after installing LightGBM from PyPI using pip install lightgbm.*

13.4.1 1. Error: setup script specifies an absolute path when installing from GitHub using python setup.py install.

```
error: Error: setup script specifies an absolute path:
/Users/Microsoft/LightGBM/python-package/lightgbm/../../lib_lightgbm.so
setup() arguments must *always* be /-separated paths relative to the setup.py
↳ directory, *never* absolute paths.
```

This error should be solved in latest version. If you still meet this error, try to remove `lightgbm.egg-info` folder in your Python-package and reinstall, or check [this thread on stackoverflow](#).

13.4.2 2. Error messages: Cannot ... before construct dataset.

I see error messages like...

```
Cannot get/set label/weight/init_score/group/num_data/num_feature before construct
↳ dataset
```

but I've already constructed a dataset by some code like:

```
train = lightgbm.Dataset(X_train, y_train)
```

or error messages like

```
Cannot set predictor/reference/categorical feature after freed raw data, set free_raw_
↳ data=False when construct Dataset to avoid this.
```

Solution: Because LightGBM constructs bin mappers to build trees, and train and valid Datasets within one Booster share the same bin mappers, categorical features and feature names etc., the Dataset objects are constructed when constructing a Booster. If you set `free_raw_data=True` (default), the raw data (with Python data struct) will be freed. So, if you want to:

- get label (or weight/init_score/group/data) before constructing a dataset, it's same as `self.label`;
- set label (or weight/init_score/group) before constructing a dataset, it's same as `self.label=some_label_array`;
- get num_data (or num_feature) before constructing a dataset, you can get data with `self.data`. Then, if your data is `numpy.ndarray`, use some code like `self.data.shape`. But do not do this after subsetting the Dataset, because you'll get always None;
- set predictor (or reference/categorical feature) after constructing a dataset, you should set `free_raw_data=False` or init a Dataset object with the same raw data.

13.4.3 3. I encounter segmentation faults (segfaults) randomly after installing LightGBM from PyPI using `pip install lightgbm`.

We are doing our best to provide universal wheels which have high running speed and are compatible with any hardware, OS, compiler, etc. at the same time. However, sometimes it's just impossible to guarantee the possibility of usage of LightGBM in any specific environment (see [Microsoft/LightGBM#1743](#)).

Therefore, the first thing you should try in case of segfaults is **compiling from the source** using `pip install --no-binary :all: lightgbm`. For the OS-specific prerequisites see [this guide](#).

Also, feel free to post a new issue in our GitHub repository. We always look at each case individually and try to find a root cause.

14.1 Algorithms

Refer to [Features](#) for understanding of important algorithms used in LightGBM.

14.2 Classes and Code Structure

14.2.1 Important Classes

| Class | Description |
|-------------------|---|
| Application | The entrance of application, including training and prediction logic |
| Bin | Data structure used for storing feature discrete values (converted from float values) |
| Boosting | Boosting interface (GBDT, DART, GOSS, etc.) |
| Config | Stores parameters and configurations |
| Dataset | Stores information of dataset |
| DatasetLoader | Used to construct dataset |
| Feature | Stores one column feature |
| Metric | Evaluation metrics |
| Network | Network interfaces and communication algorithms |
| ObjectiveFunction | Objective functions used to train |
| Tree | Stores information of tree model |
| TreeLearner | Used to learn trees |

14.2.2 Code Structure

| Path | Description |
|--------------------------------|--|
| <code>./include</code> | Header files |
| <code>./include/Utils</code> | Some common functions |
| <code>./src/application</code> | Implementations of training and prediction logic |
| <code>./src/boosting</code> | Implementations of Boosting |
| <code>./src/io</code> | Implementations of IO related classes, including <code>Bin</code> , <code>Config</code> , <code>Dataset</code> , <code>DatasetLoader</code> , <code>Feature</code> and <code>Tree</code> |
| <code>./src/metric</code> | Implementations of metrics |
| <code>./src/network</code> | Implementations of network functions |
| <code>./src/objective</code> | Implementations of objective functions |
| <code>./src/treelearner</code> | Implementations of tree learners |

14.2.3 Documents API

Refer to [docs README](#).

14.3 C API

Refer to [C API](#) or the comments in `c_api.h` file, from which the documentation is generated.

14.4 High Level Language Package

See the implementations at [Python-package](#) and [R-package](#).

14.5 Questions

Refer to [FAQ](#).

Also feel free to open [issues](#) if you met problems.

GPU Tuning Guide and Performance Comparison

15.1 How It Works?

In LightGBM, the main computation cost during training is building the feature histograms. We use an efficient algorithm on GPU to accelerate this process. The implementation is highly modular, and works for all learning tasks (classification, ranking, regression, etc). GPU acceleration also works in distributed learning settings. GPU algorithm implementation is based on OpenCL and can work with a wide range of GPUs.

15.2 Supported Hardware

We target AMD Graphics Core Next (GCN) architecture and NVIDIA Maxwell and Pascal architectures. Most AMD GPUs released after 2012 and NVIDIA GPUs released after 2014 should be supported. We have tested the GPU implementation on the following GPUs:

- AMD RX 480 with AMDGPU-pro driver 16.60 on Ubuntu 16.10
- AMD R9 280X (aka Radeon HD 7970) with fglrx driver 15.302.2301 on Ubuntu 16.10
- NVIDIA GTX 1080 with driver 375.39 and CUDA 8.0 on Ubuntu 16.10
- NVIDIA Titan X (Pascal) with driver 367.48 and CUDA 8.0 on Ubuntu 16.04
- NVIDIA Tesla M40 with driver 375.39 and CUDA 7.5 on Ubuntu 16.04

Using the following hardware is discouraged:

- NVIDIA Kepler (K80, K40, K20, most GeForce GTX 700 series GPUs) or earlier NVIDIA GPUs. They don't support hardware atomic operations in local memory space and thus histogram construction will be slow.
- AMD VLIW4-based GPUs, including Radeon HD 6xxx series and earlier GPUs. These GPUs have been discontinued for years and are rarely seen nowadays.

15.3 How to Achieve Good Speedup on GPU

1. You want to run a few datasets that we have verified with good speedup (including Higgs, epsilon, Bosch, etc) to ensure your setup is correct. If you have multiple GPUs, make sure to set `gpu_platform_id` and `gpu_device_id` to use the desired GPU. Also make sure your system is idle (especially when using a shared computer) to get accuracy performance measurements.
2. GPU works best on large scale and dense datasets. If dataset is too small, computing it on GPU is inefficient as the data transfer overhead can be significant. For dataset with a mixture of sparse and dense features, you can control the `sparse_threshold` parameter to make sure there are enough dense features to process on the GPU. If you have categorical features, use the `categorical_column` option and input them into LightGBM directly; do not convert them into one-hot variables. Make sure to check the run log and look at the reported number of sparse and dense features.
3. To get good speedup with GPU, it is suggested to use a smaller number of bins. Setting `max_bin=63` is recommended, as it usually does not noticeably affect training accuracy on large datasets, but GPU training can be significantly faster than using the default bin size of 255. For some dataset, even using 15 bins is enough (`max_bin=15`); using 15 bins will maximize GPU performance. Make sure to check the run log and verify that the desired number of bins is used.
4. Try to use single precision training (`gpu_use_dp=false`) when possible, because most GPUs (especially NVIDIA consumer GPUs) have poor double-precision performance.

15.4 Performance Comparison

We evaluate the training performance of GPU acceleration on the following datasets:

| Data | Task | Link | #Exam- ples | #Fea- tures | Comments |
|-----------|-------------------------------------|-----------------------|----------------|----------------|---|
| Higgs | Binary classification | link1 | 10,500,000 | 28 | use last 500,000 samples as test set |
| Epsilon | Binary classification | link2 | 400,000 | 2,000 | use the provided test set |
| Bosch | Binary classification | link3 | 1,000,000 | 968 | use the provided test set |
| Yahoo LTR | Learning to rank | link4 | 473,134 | 700 | set1.train as train, set1.test as test |
| MS LTR | Learning to rank | link5 | 2,270,296 | 137 | {S1,S2,S3} as train set, {S5} as test set |
| Expo | Binary classification (Categorical) | link6 | 11,000,000 | 700 | use last 1,000,000 as test set |

We used the following hardware to evaluate the performance of LightGBM GPU training. Our CPU reference is **a high-end dual socket Haswell-EP Xeon server with 28 cores**; GPUs include a budget GPU (RX 480) and a mainstream (GTX 1080) GPU installed on the same server. It is worth mentioning that **the GPUs used are not the best GPUs in the market**; if you are using a better GPU (like AMD RX 580, NVIDIA GTX 1080 Ti, Titan X Pascal, Titan Xp, Tesla P100, etc), you are likely to get a better speedup.

| Hardware | Peak FLOPS | Peak Memory BW | Cost (MSRP) |
|------------------------------|--------------|----------------|-------------|
| AMD Radeon RX 480 | 5,161 GFLOPS | 256 GB/s | \$199 |
| NVIDIA GTX 1080 | 8,228 GFLOPS | 320 GB/s | \$499 |
| 2x Xeon E5-2683v3 (28 cores) | 1,792 GFLOPS | 133 GB/s | \$3,692 |

During benchmarking on CPU we used only 28 physical cores of the CPU, and did not use hyper-threading cores,

because we found that using too many threads actually makes performance worse. The following shows the training configuration we used:

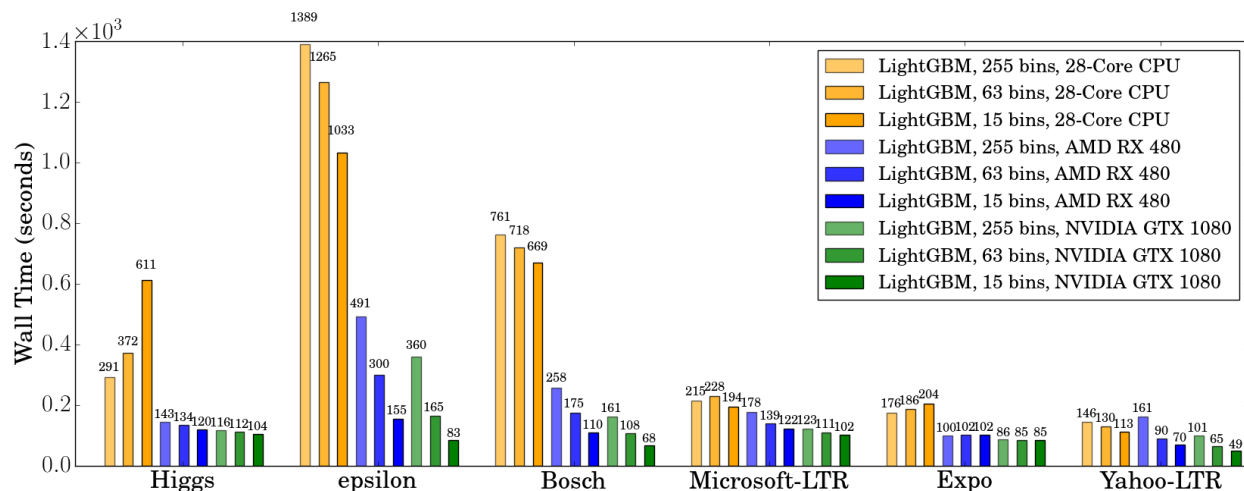
```
max_bin = 63
num_leaves = 255
num_iterations = 500
learning_rate = 0.1
tree_learner = serial
task = train
is_training_metric = false
min_data_in_leaf = 1
min_sum_hessian_in_leaf = 100
ndcg_eval_at = 1,3,5,10
sparse_threshold=1.0
device = gpu
gpu_platform_id = 0
gpu_device_id = 0
num_thread = 28
```

We use the configuration shown above, except for the Bosch dataset, we use a smaller `learning_rate=0.015` and set `min_sum_hessian_in_leaf=5`. For all GPU training we set `sparse_threshold=1`, and vary the max number of bins (255, 63 and 15). The GPU implementation is from commit [0bb4a82](#) of LightGBM, when the GPU support was just merged in.

The following table lists the accuracy on test set that CPU and GPU learner can achieve after 500 iterations. GPU with the same number of bins can achieve a similar level of accuracy as on the CPU, despite using single precision arithmetic. For most datasets, using 63 bins is sufficient.

| | CPU 255 bins | CPU 63 bins | CPU 15 bins | GPU 255 bins | GPU 63 bins | GPU 15 bins |
|---------------------------------|-----------------|----------------|----------------|-----------------|----------------|----------------|
| Higgs AUC | 0.845612 | 0.845239 | 0.841066 | 0.845612 | 0.845209 | 0.840748 |
| Epsilon AUC | 0.950243 | 0.949952 | 0.948365 | 0.950057 | 0.949876 | 0.948365 |
| Yahoo-LTR NDCG ₁ | 0.730824 | 0.730165 | 0.729647 | 0.730936 | 0.732257 | 0.73114 |
| Yahoo-LTR NDCG ₃ | 0.738687 | 0.737243 | 0.736445 | 0.73698 | 0.739474 | 0.735868 |
| Yahoo-LTR NDCG ₅ | 0.756609 | 0.755729 | 0.754607 | 0.756206 | 0.757007 | 0.754203 |
| Yahoo-LTR NDCG ₁₀ | 0.79655 | 0.795827 | 0.795273 | 0.795894 | 0.797302 | 0.795584 |
| Expo AUC | 0.776217 | 0.771566 | 0.743329 | 0.776285 | 0.77098 | 0.744078 |
| MS-LTR NDCG ₁ | 0.521265 | 0.521392 | 0.518653 | 0.521789 | 0.522163 | 0.516388 |
| MS-LTR NDCG ₃ | 0.503153 | 0.505753 | 0.501697 | 0.503886 | 0.504089 | 0.501691 |
| MS-LTR NDCG ₅ | 0.509236 | 0.510391 | 0.507193 | 0.509861 | 0.510095 | 0.50663 |
| MS-LTR NDCG ₁₀ | 0.527835 | 0.527304 | 0.524603 | 0.528009 | 0.527059 | 0.524722 |
| Bosch AUC | 0.718115 | 0.721791 | 0.716677 | 0.717184 | 0.724761 | 0.717005 |

We record the wall clock time after 500 iterations, as shown in the figure below:



When using a GPU, it is advisable to use a bin size of 63 rather than 255, because it can speed up training significantly without noticeably affecting accuracy. On CPU, using a smaller bin size only marginally improves performance, sometimes even slows down training, like in Higgs (we can reproduce the same slowdown on two different machines, with different GCC versions). We found that GPU can achieve impressive acceleration on large and dense datasets like Higgs and Epsilon. Even on smaller and sparse datasets, a *budget* GPU can still compete and be faster than a 28-core Haswell server.

15.5 Memory Usage

The next table shows GPU memory usage reported by `nvidia-smi` during training with 63 bins. We can see that even the largest dataset just uses about 1 GB of GPU memory, indicating that our GPU implementation can scale to huge datasets over 10x larger than Bosch or Epsilon. Also, we can observe that generally a larger dataset (using more GPU memory, like Epsilon or Bosch) has better speedup, because the overhead of invoking GPU functions becomes significant when the dataset is small.

| Datasets | Higgs | Epsilon | Bosch | MS-LTR | Expo | Yahoo-LTR |
|-----------------------|-------|---------|-------|--------|------|-----------|
| GPU Memory Usage (MB) | 611 | 901 | 1067 | 413 | 405 | 291 |

15.6 Further Reading

You can find more details about the GPU algorithm and benchmarks in the following article:

Huan Zhang, Si Si and Cho-Jui Hsieh. [GPU Acceleration for Large-scale Tree Boosting](#). SysML Conference, 2018.

GPU SDK Correspondence and Device Targeting Table

16.1 GPU Targets Table

OpenCL is a universal massively parallel programming framework that targets to multiple backends (GPU, CPU, FPGA, etc). Basically, to use a device from a vendor, you have to install drivers from that specific vendor. Intel's and AMD's OpenCL runtime also include x86 CPU target support. NVIDIA's OpenCL runtime only supports NVIDIA GPU (no CPU support). In general, OpenCL CPU backends are quite slow, and should be used for testing and debugging only.

You can find below a table of correspondence:

| SDK | CPU Intel/AMD | GPU Intel | GPU AMD | GPU NVIDIA |
|--------------------------------------|---------------|---------------|---------------|---------------|
| Intel SDK for OpenCL | Supported | Supported | Not Supported | Not Supported |
| AMD APP SDK * | Supported | Not Supported | Supported | Not Supported |
| NVIDIA CUDA Toolkit | Not Supported | Not Supported | Not Supported | Supported |

Legend:

* AMD APP SDK is deprecated. On Windows, OpenCL is included in AMD graphics driver. On Linux, newer generation AMD cards are supported by the [ROCm](#) driver. You can download an archived copy of AMD APP SDK for Linux from [our GitHub repo](#).

16.2 Query OpenCL Devices in Your System

Your system might have multiple GPUs from different vendors ("platforms") installed. Setting up LightGBM GPU device requires two parameters: [OpenCL Platform ID](#) (`gpu_platform_id`) and [OpenCL Device ID](#) (`gpu_device_id`). Generally speaking, each vendor provides an OpenCL platform, and devices from the same vendor have different device IDs under that platform. For example, if your system has an Intel integrated GPU and two discrete GPUs from AMD, you will have two OpenCL platforms (with `gpu_platform_id=0` and

gpu_platform_id=1). If the platform 0 is Intel, it has one device (gpu_device_id=0) representing the Intel GPU; if the platform 1 is AMD, it has two devices (gpu_device_id=0, gpu_device_id=1) representing the two AMD GPUs. If you have a discrete GPU by AMD/NVIDIA and an integrated GPU by Intel, make sure to select the correct gpu_platform_id to use the discrete GPU as it usually provides better performance.

On Windows, OpenCL devices can be queried using [GPUCapsViewer](#), under the OpenCL tab. Note that the platform and device IDs reported by this utility start from 1. So you should minus the reported IDs by 1.

On Linux, OpenCL devices can be listed using the `clinfo` command. On Ubuntu, you can install `clinfo` by executing `sudo apt-get install clinfo`.

16.3 Examples

We provide test R code below, but you can use the language of your choice with the examples of your choices:

```
library(lightgbm)
data(agaricus.train, package = "lightgbm")
train <- agaricus.train
train$data[, 1] <- 1:6513
dtrain <- lgb.Dataset(train$data, label = train$label)
data(agaricus.test, package = "lightgbm")
test <- agaricus.test
dtest <- lgb.Dataset.create.valid(dtrain, test$data, label = test$label)
valids <- list(test = dtest)

params <- list(objective = "regression",
               metric = "rmse",
               device = "gpu",
               gpu_platform_id = 0,
               gpu_device_id = 0,
               nthread = 1,
               boost_from_average = FALSE,
               num_tree_per_iteration = 10,
               max_bin = 32)
model <- lgb.train(params,
                  dtrain,
                  2,
                  valids,
                  min_data = 1,
                  learning_rate = 1,
                  early_stopping_rounds = 10)
```

Make sure you list the OpenCL devices in your system and set `gpu_platform_id` and `gpu_device_id` correctly. In the following examples, our system has 1 GPU platform (`gpu_platform_id = 0`) from AMD APP SDK. The first device `gpu_device_id = 0` is a GPU device (AMD Oland), and the second device `gpu_device_id = 1` is the x86 CPU backend.

Example of using GPU (`gpu_platform_id = 0` and `gpu_device_id = 0` in our system):

```
> params <- list(objective = "regression",
+               metric = "rmse",
+               device = "gpu",
+               gpu_platform_id = 0,
+               gpu_device_id = 0,
+               nthread = 1,
+               boost_from_average = FALSE,
```

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```

+         num_tree_per_iteration = 10,
+         max_bin = 32)
> model <- lgb.train(params,
+                   dtrain,
+                   2,
+                   valids,
+                   min_data = 1,
+                   learning_rate = 1,
+                   early_stopping_rounds = 10)
[LightGBM] [Info] This is the GPU trainer!!
[LightGBM] [Info] Total Bins 232
[LightGBM] [Info] Number of data: 6513, number of used features: 116
[LightGBM] [Info] Using GPU Device: Oland, Vendor: Advanced Micro Devices, Inc.
[LightGBM] [Info] Compiling OpenCL Kernel with 16 bins...
[LightGBM] [Info] GPU programs have been built
[LightGBM] [Info] Size of histogram bin entry: 12
[LightGBM] [Info] 40 dense feature groups (0.12 MB) transferred to GPU in 0.004211_
↪secs. 76 sparse feature groups.
[LightGBM] [Info] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Trained a tree with leaves=16 and max_depth=8
[1]:   test's rmse:1.10643e-17
[LightGBM] [Info] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Trained a tree with leaves=7 and max_depth=5
[2]:   test's rmse:0

```

Running on OpenCL CPU backend devices is in generally slow, and we observe crashes on some Windows and macOS systems. Make sure you check the Using GPU Device line in the log and it is not using a CPU. The above log shows that we are using Oland GPU from AMD and not CPU.

Example of using CPU (gpu_platform_id = 0, gpu_device_id = 1). The GPU device reported is Intel(R) Core(TM) i7-4600U CPU, so it is using the CPU backend rather than a real GPU.

```

> params <- list(objective = "regression",
+               metric = "rmse",
+               device = "gpu",
+               gpu_platform_id = 0,
+               gpu_device_id = 1,
+               nthread = 1,
+               boost_from_average = FALSE,
+               num_tree_per_iteration = 10,
+               max_bin = 32)
> model <- lgb.train(params,
+                   dtrain,
+                   2,
+                   valids,
+                   min_data = 1,
+                   learning_rate = 1,
+                   early_stopping_rounds = 10)
[LightGBM] [Info] This is the GPU trainer!!
[LightGBM] [Info] Total Bins 232
[LightGBM] [Info] Number of data: 6513, number of used features: 116
[LightGBM] [Info] Using requested OpenCL platform 0 device 1
[LightGBM] [Info] Using GPU Device: Intel(R) Core(TM) i7-4600U CPU @ 2.10GHz, Vendor:_
↪GenuineIntel
[LightGBM] [Info] Compiling OpenCL Kernel with 16 bins...
[LightGBM] [Info] GPU programs have been built
[LightGBM] [Info] Size of histogram bin entry: 12

```

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```
[LightGBM] [Info] 40 dense feature groups (0.12 MB) transferred to GPU in 0.004540_
↪secs. 76 sparse feature groups.
[LightGBM] [Info] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Trained a tree with leaves=16 and max_depth=8
[1]:      test's rmse:1.10643e-17
[LightGBM] [Info] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Trained a tree with leaves=7 and max_depth=5
[2]:      test's rmse:0
```

Known issues:

- Using a bad combination of `gpu_platform_id` and `gpu_device_id` can potentially lead to a **crash** due to OpenCL driver issues on some machines (you will lose your entire session content). Beware of it.
- On some systems, if you have integrated graphics card (Intel HD Graphics) and a dedicated graphics card (AMD, NVIDIA), the dedicated graphics card will automatically override the integrated graphics card. The workaround is to disable your dedicated graphics card to be able to use your integrated graphics card.

GPU Windows Compilation

This guide is for the MinGW build.

For the MSVC (Visual Studio) build with GPU, please refer to [Installation Guide](#). (We recommend you to use this since it is much easier).

17.1 Install LightGBM GPU version in Windows (CLI / R / Python), using MinGW/gcc

This is for a vanilla installation of Boost, including full compilation steps from source without precompiled libraries.

Installation steps (depends on what you are going to do):

- Install the appropriate OpenCL SDK
- Install MinGW
- Install Boost
- Install Git
- Install CMake
- Create LightGBM binaries
- Debugging LightGBM in CLI (if GPU is crashing or any other crash reason)

If you wish to use another compiler like Visual Studio C++ compiler, you need to adapt the steps to your needs.

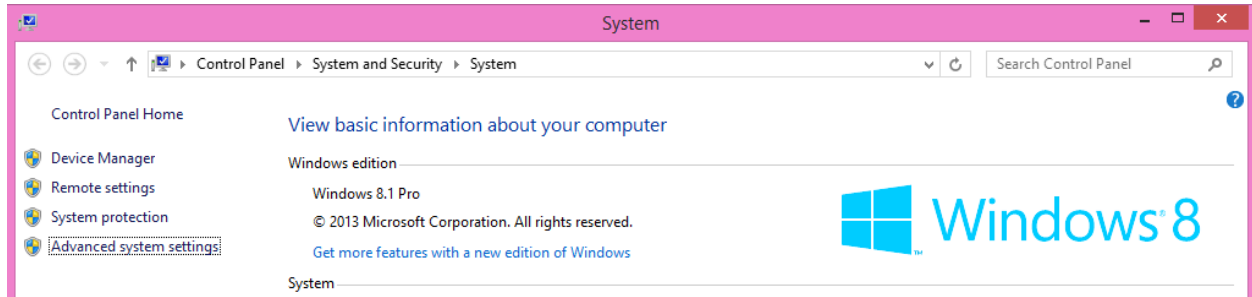
For this compilation tutorial, we are using AMD SDK for our OpenCL steps. However, you are free to use any OpenCL SDK you want, you just need to adjust the PATH correctly.

You will also need administrator rights. This will not work without them.

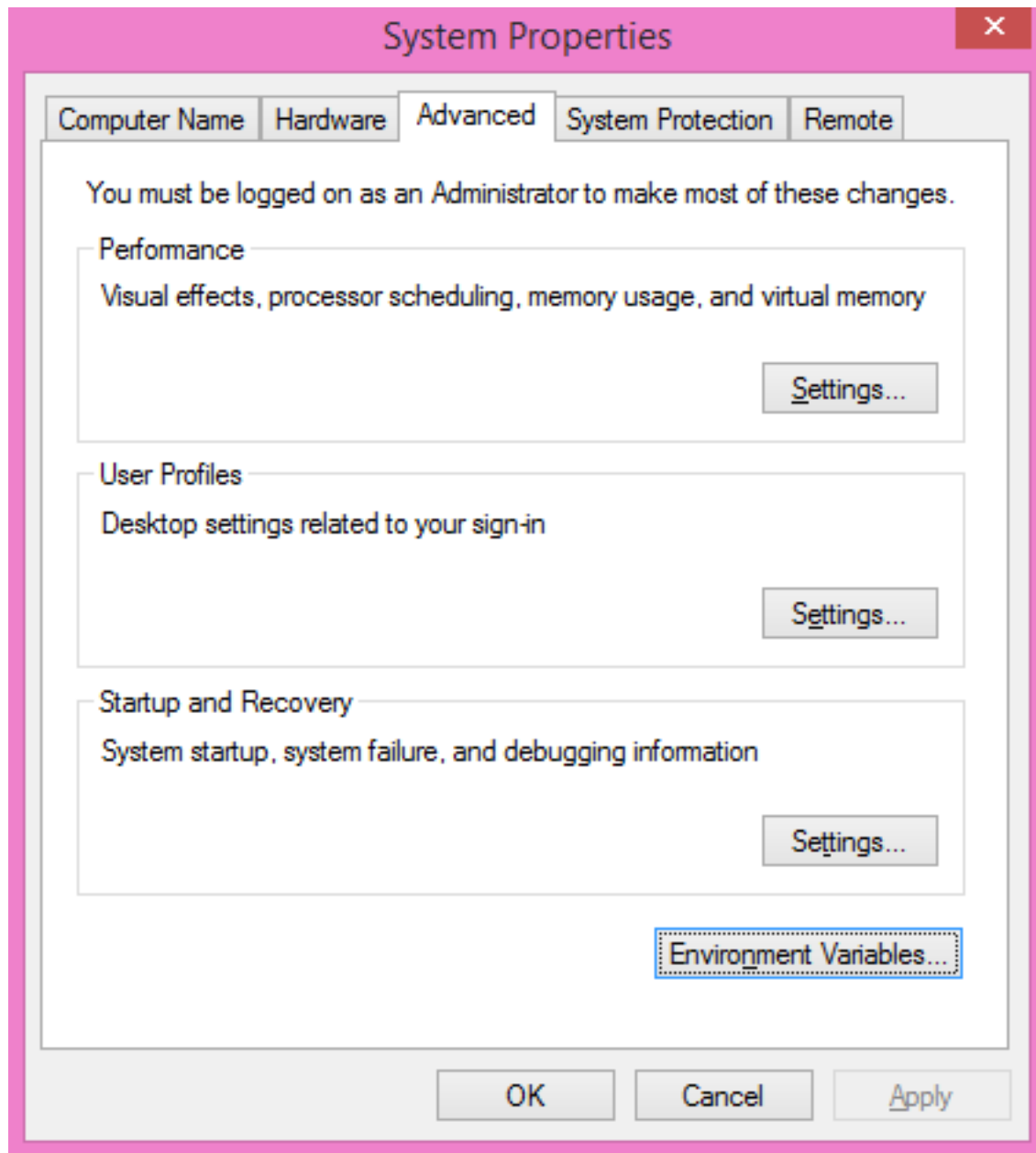
At the end, you can restore your original PATH.

17.1.1 Modifying PATH (for newbies)

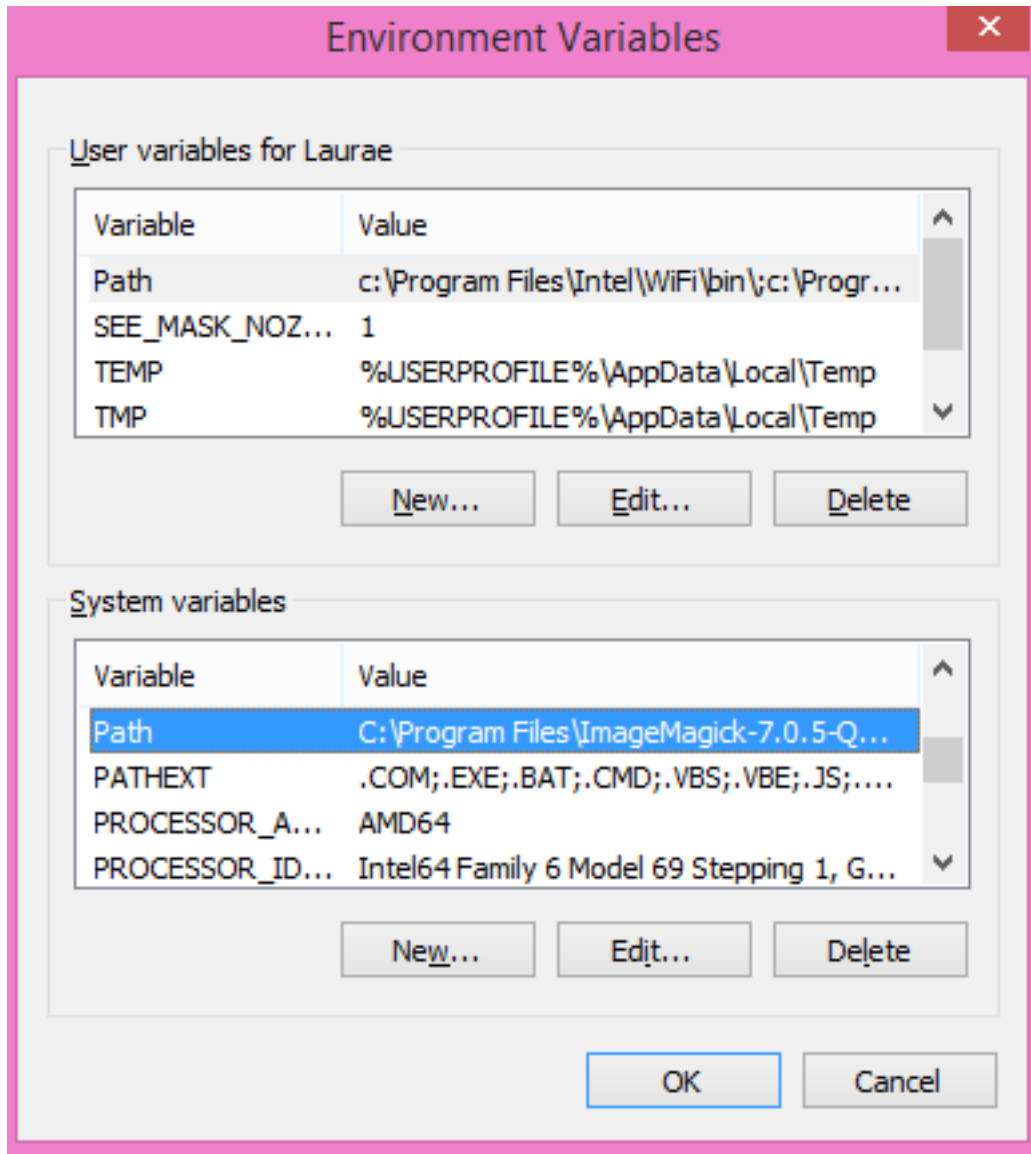
To modify PATH, just follow the pictures after going to the Control Panel:



Then, go to Advanced > Environment Variables...:



Under System variables, the variable Path:



Antivirus Performance Impact

Does not apply to you if you do not use a third-party antivirus nor the default preinstalled antivirus on Windows.

Windows Defender or any other antivirus will have a significant impact on the speed you will be able to perform the steps. It is recommended to **turn them off temporarily** until you finished with building and setting up everything, then turn them back on, if you are using them.

17.1.2 OpenCL SDK Installation

Installing the appropriate OpenCL SDK requires you to download the correct vendor source SDK. You need to know what you are going to use LightGBM!

- For running on Intel, get [Intel SDK for OpenCL](#) (NOT RECOMMENDED).
- For running on AMD, get [AMD APP SDK](#) (you may want to replace the `OpenCL.dll` from GPU driver package with the one from the SDK, if the one shipped with the driver lacks some functions).
- For running on NVIDIA, get [CUDA Toolkit](#).
- Or you can try to use [Khronos official OpenCL headers](#), the CMake module would automatically find the OpenCL library used in your system, though the result may be not portable.

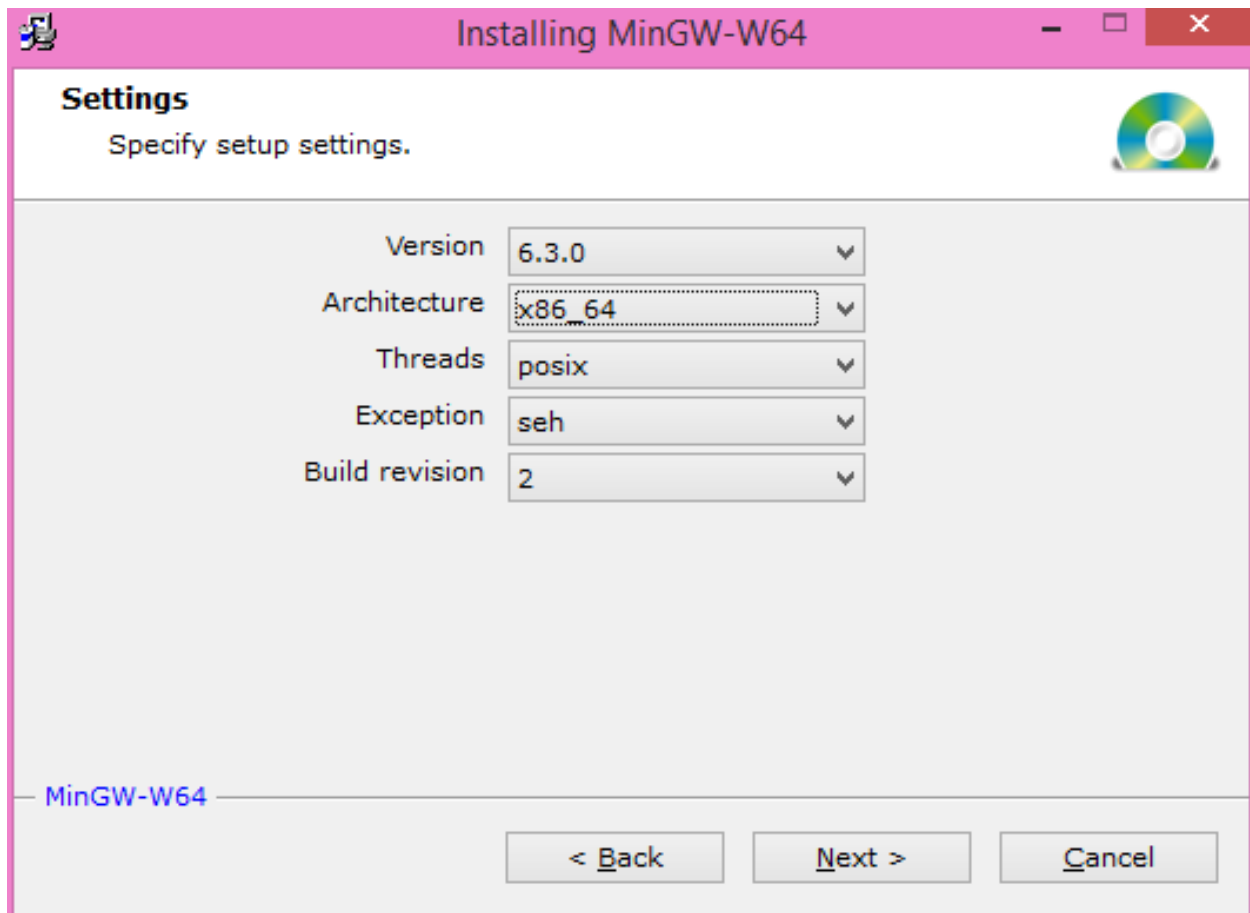
Further reading and correspondence table (especially if you intend to use cross-platform devices, like Intel CPU with AMD APP SDK): [GPU SDK Correspondence and Device Targeting Table](#).

Warning: using Intel OpenCL is not recommended and may crash your machine due to being non compliant to OpenCL standards. If your objective is to use LightGBM + OpenCL on CPU, please use AMD APP SDK instead (it can run also on Intel CPUs without any issues).

17.1.3 MinGW Correct Compiler Selection

If you are expecting to use LightGBM without R, you need to install MinGW. Installing MinGW is straightforward, download [this](#).

Make sure you are using the `x86_64` architecture, and do not modify anything else. You may choose a version other than the most recent one if you need a previous MinGW version.



Then, add to your PATH the following (to adjust to your MinGW version):

```
C:\Program Files\mingw-w64\x86_64-5.3.0-posix-seh-rt_v4-rev0\mingw64\bin
```

Warning: R users (even if you do not want LightGBM for R)

If you have RTools and MinGW installed, and wish to use LightGBM in R, get rid of MinGW from PATH (to keep: `c:\Rtools\bin;c:\Rtools\mingw_32\bin` for 32-bit R installation, `c:\Rtools\bin;c:\Rtools\mingw_64\bin` for 64-bit R installation).

You can check which MinGW version you are using by running the following in a command prompt: `gcc -v`:

```
C:\>cd C:\Program Files\Git\bin
Administrator: Command Prompt

C:\Program Files\Git\bin>C:\nohost>nohost 1.63 @ntools build>gcc -v
Using built-in specs.
COLLECT_GCC=gcc
COLLECT_LTO_WRAPPER=c:/tools/mingw32/bin/./libexec/gcc/i686-w64-mingw32/4.9.3/lto-wrapper.exe
target=i686-w64-mingw32
configured with:
  /usr/bin/./configure --host=i686-w64-mingw32 --build=i686-w64-mingw32 --target=i686-w64-mingw32 --prefix=/mingw32 --with-sysoctool=/home/Jeroen/mingw-gcc-4.9.3/i686-493-posix-dwarf-v2-v3/sysoctool --with-gxx-include-dir=/mingw32/i686-w64-mingw32/include/c++ --enable-static --disable-shared --disable-multilib --enable-languages=c,c++,fortran,objc --enable-languages-c++-time-yes --enable-threads=posix --enable-libgomp --enable-libatomic --enable-libc --enable-checking=release --enable-fully-dynamic-string --enable-version-specific-runtime-libs --disable-kill-exceptions --with-dwarf2 --disable-lto --version-check --disable-loop-version-check --disable-libstdc++-pch --disable-libstdc++-debug --enable-bootstrap --disable-rpath --disable-win32-registry --disable-nls --disable-werror --disable-symvers --with-gnu-as --with-gnu-ld --with-arch=i686 --with-tune=generic --with-libiconv --with-system-zlib --with-gmp=/home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static --with-mpfr=/home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static --with-isl=/home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static --with-cloog=/home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static --enable-cloog-backend=isl --with-pkgversion='i686-w64-mingw32, Built by MinGW-V64 project' --with-bugurl=http://sourceforge.net/projects/mingw-w64 CFLAGS='-O2' pipe 1 /home/Jeroen/mingw-gcc-4.9.3/i686-493-posix-dwarf-v2-v3/sysoctool --opt-include 1 /home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static/include 1 /home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static/include CXXFLAGS='-O2' pipe 1 /home/Jeroen/mingw-gcc-4.9.3/i686-493-posix-dwarf-v2-v3/sysoctool --opt-include 1 /home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static/include 1 /home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static/include CPPFLAGS=LDLIBS='-pipe 1 /home/Jeroen/mingw-gcc-4.9.3/i686-493-posix-dwarf-v2-v3/sysoctool --opt-include 1 /home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static/include 1 /home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static/include'
Thread model: posix
gcc version 4.9.3 (i686-w64-mingw32, Built by MinGW-V64 project)
```

To check whether you need 32-bit or 64-bit MinGW for R, install LightGBM as usual and check for the following:

```
* installing *source* package 'lightgbm' ...
** libs
c:/Rtools/mingw_64/bin/g++
```

If it says mingw_64 then you need the 64-bit version (PATH with c:\Rtools\bin; c:\Rtools\mingw_64\bin), otherwise you need the 32-bit version (c:\Rtools\bin; c:\Rtools\mingw_32\bin), the latter being a very rare and untested case.

Quick installation of LightGBM can be done using:

```
devtools::install_github("Microsoft/LightGBM", subdir = "R-package")
```

17.1.4 Download the prebuilt Boost

Download [Prebuilt Boost x86_64](#) or [Prebuilt Boost i686](#) and unpack them with [7zip](#), alternatively you can build Boost from source.

17.1.5 Boost Compilation

Installing Boost requires to download Boost and to install it. It takes about 10 minutes to several hours depending on your CPU speed and network speed.

We will assume an installation in `C:\boost` and a general installation (like in Unix variants: without versioning and without type tags).

There is one mandatory step to check the compiler:

- **Warning:** if you want the R installation: If you have already MinGW in your PATH variable, get rid of it (you will link to the wrong compiler otherwise).

- **Warning:** if you want the CLI installation: If you have already Rtools in your PATH variable, get rid of it (you will link to the wrong compiler otherwise).
- R installation must have Rtools in PATH
- CLI / Python installation must have MinGW (not Rtools) in PATH

In addition, assuming you are going to use `C:\boost` for the folder path, you should add now already the following to PATH: `C:\boost\boost-build\bin`, `C:\boost\boost-build\include\boost`. Adjust `C:\boost` if you install it elsewhere.

We can now start downloading and compiling the required Boost libraries:

- Download [Boost](#) (for example, the filename for 1.63.0 version is `boost_1_63_0.zip`)
- Extract the archive to `C:\boost`
- Open a command prompt, and run

```
cd C:\boost\boost_1_63_0\tools\build
bootstrap.bat gcc
b2 install --prefix="C:\boost\boost-build" toolset=gcc
cd C:\boost\boost_1_63_0
```

To build the Boost libraries, you have two choices for command prompt:

- If you have only one single core, you can use the default

```
b2 install --build_dir="C:\boost\boost-build" --prefix="C:\boost\boost-build"
↪toolset=gcc --with=filesystem,system threading=multi --layout=system release
```

- If you want to do a multithreaded library building (faster), add `-j N` by replacing `N` by the number of cores/threads you have. For instance, for 2 cores, you would do

```
b2 install --build_dir="C:\boost\boost-build" --prefix="C:\boost\boost-build"
↪toolset=gcc --with=filesystem,system threading=multi --layout=system release -j
↪2
```

Ignore all the errors popping up, like Python, etc., they do not matter for us.

Your folder should look like this at the end (not fully detailed):

```
- C
|--- boost
|----- boost_1_63_0
|----- some folders and files
|----- boost-build
|----- bin
|----- include
|----- boost
|----- lib
|----- share
```

This is what you should (approximately) get at the end of Boost compilation:

```

bin.v2\libs\type_erasure\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\libboost_type_erasure-ngw53-mt-d-1_63.a
1 file(s) copied.
common.mkdir bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug
common.mkdir bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static
common.mkdir bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\instantiate_cpp_exprgrammar.o
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\instantiate_cpp_grammar.o
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\instantiate_cpp_literalgrs.o
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\instantiate_defined_grammar.o
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\instantiate_predef_macros.o
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\instantiate_re2c_lexer.o
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\instantiate_re2c_lexer_str.o
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\token_ids.o
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\wave_config_constant.o
common.mkdir bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\cplexer\re2clex
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\cplexer\re2clex\aq.o
gcc.compile.c++ bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\cplexer\re2clex\cpp_re.o
gcc.archive bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\libboost_wave-ngw53-mt-d-1_63.a
common.copy C:\boost\boost-build\lib\libboost_wave-ngw53-mt-d-1_63.a
bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\libboost_wave-ngw53-mt-d-1_63.a
1 file(s) copied.
...updated 14621 targets...
C:\boost\boost 1_63 0

```

If you are getting an error:

- Wipe your Boost directory
- Close the command prompt
- Make sure you added C:\boost\boost-build\bin, C:\boost\boost-build\include\boost to your PATH (adjust accordingly if you use another folder)
- Do the Boost compilation steps again (extract => command prompt => cd => bootstrap => b2 => cd => b2)

17.1.6 Git Installation

Installing Git for Windows is straightforward, use the following [link](#).

Now, we can fetch LightGBM repository for GitHub. Run Git Bash and the following command:

```
cd C:/
mkdir github_repos
cd github_repos
git clone --recursive https://github.com/microsoft/LightGBM
```

Your LightGBM repository copy should now be under C:\github_repos\LightGBM. You are free to use any folder you want, but you have to adapt.

Keep Git Bash open.

17.1.7 CMake Installation, Configuration, Generation

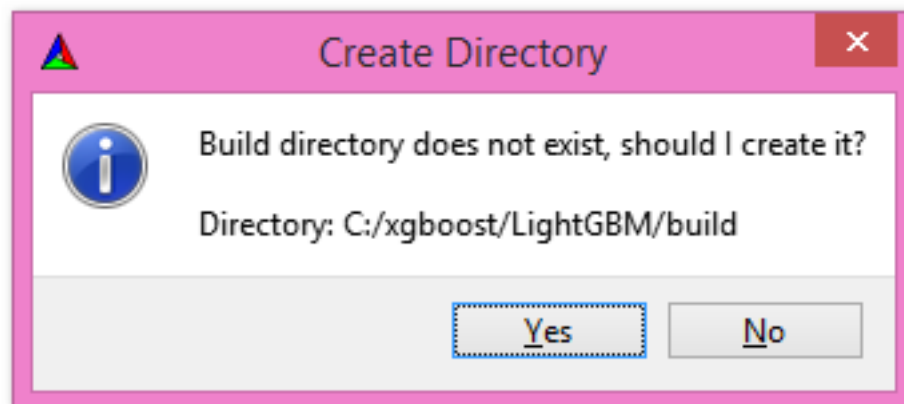
CLI / Python users only

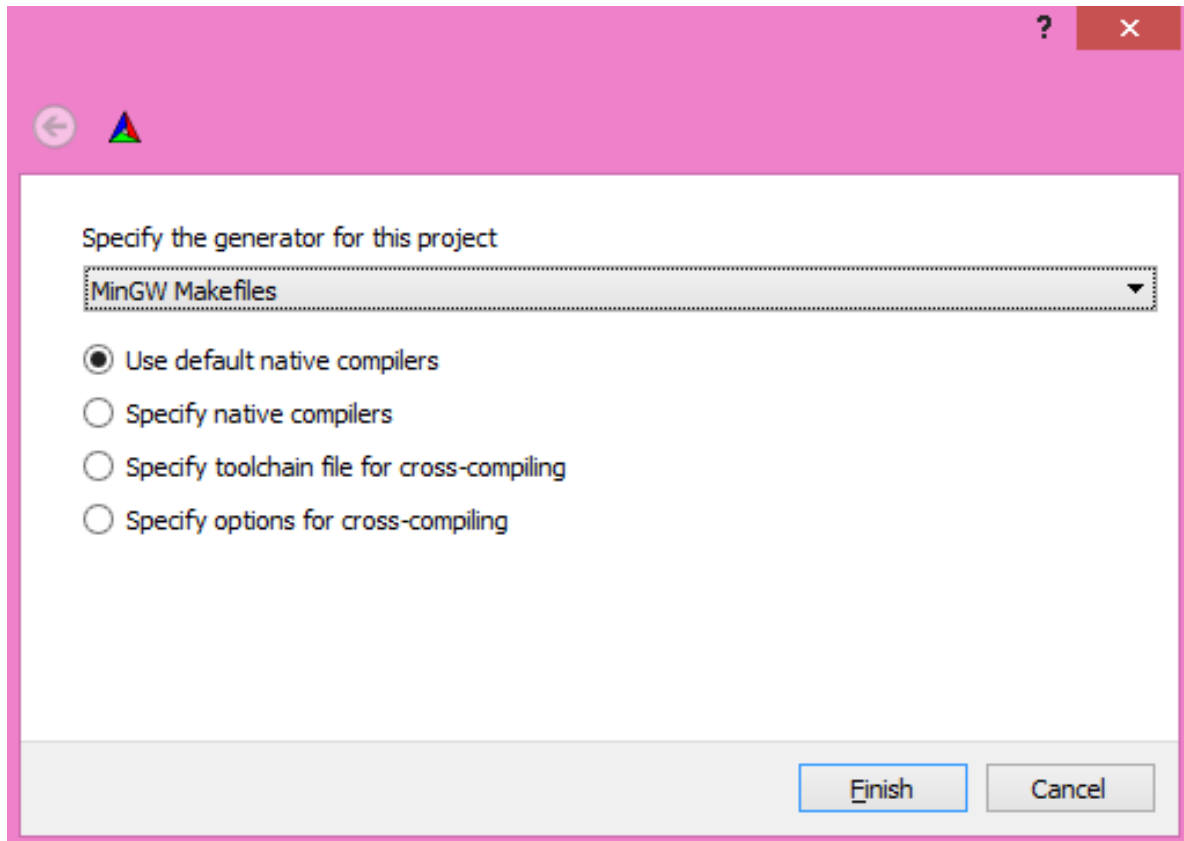
Installing CMake requires one download first and then a lot of configuration for LightGBM:

Binary distributions:

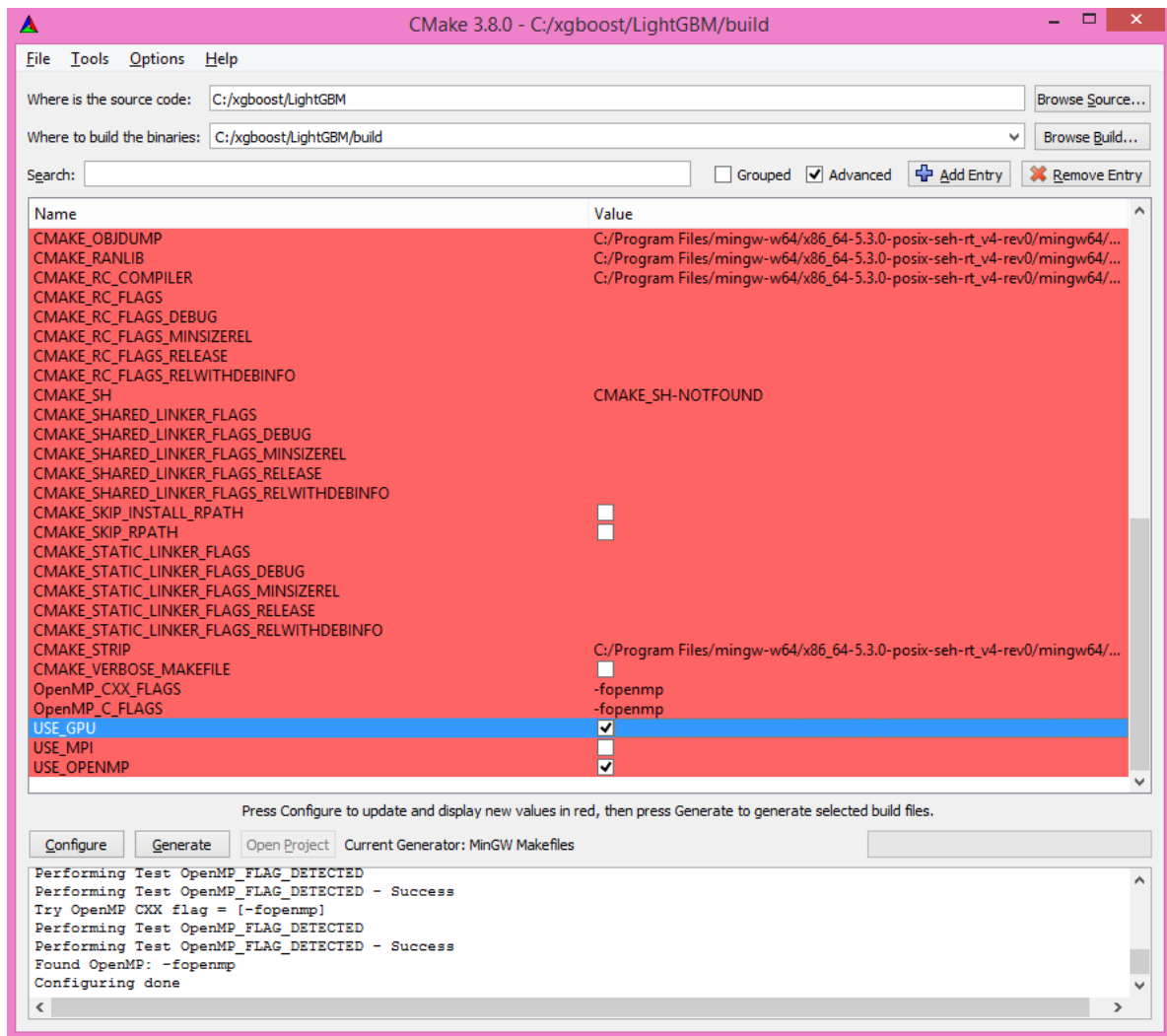
| Platform | Files |
|---|---|
| Windows win64-x64 Installer: Installer tool has changed. Uninstall CMake 3.4 or lower first! | cmake-3.8.0-win64-x64.msi |

- Download [CMake](#) (3.8 or higher)
- Install CMake
- Run cmake-gui
- Select the folder where you put LightGBM for Where is the source code, default using our steps would be C:/github_repos/LightGBM
- Copy the folder name, and add /build for “Where to build the binaries”, default using our steps would be C:/github_repos/LightGBM/build
- Click Configure



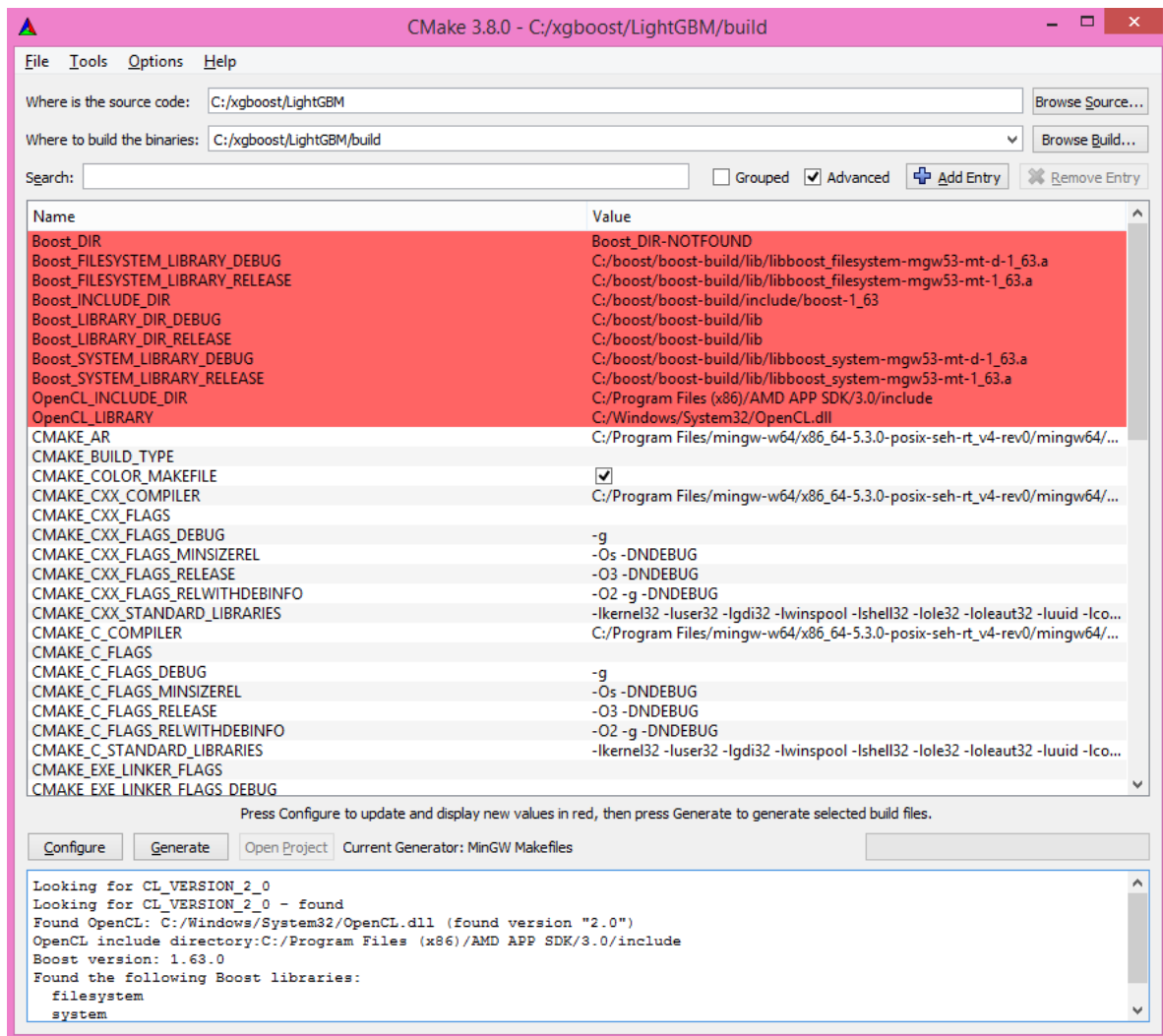


- Lookup for `USE_GPU` and check the checkbox



- Click Configure

You should get (approximately) the following after clicking Configure:



```
Looking for CL_VERSION_2_0
Looking for CL_VERSION_2_0 - found
Found OpenCL: C:/Windows/System32/OpenCL.dll (found version "2.0")
OpenCL include directory: C:/Program Files (x86)/AMD APP SDK/3.0/include
Boost version: 1.63.0
Found the following Boost libraries:
  filesystem
  system
Configuring done
```

- Click Generate to get the following message:

```
Generating done
```

This is straightforward, as CMake is providing a large help into locating the correct elements.

17.1.8 LightGBM Compilation (CLI: final step)

Installation in CLI

CLI / Python users

Creating LightGBM libraries is very simple as all the important and hard steps were done before.

You can do everything in the Git Bash console you left open:

- If you closed Git Bash console previously, run this to get back to the build folder:

```
cd C:/github_repos/LightGBM/build
```

- If you did not close the Git Bash console previously, run this to get to the build folder:

```
cd LightGBM/build
```

- Setup MinGW as make using

```
alias make='mingw32-make'
```

otherwise, beware error and name clash!

- In Git Bash, run make and see LightGBM being installing!

```

.hpp:18,
        from C:\xgboost\LightGBM\src\treelearner\gpu_tree_learner.h:27,
        from C:\xgboost\LightGBM\src\treelearner\parallel_tree_learner.
h:8,
        from C:\xgboost\LightGBM\src\treelearner\voting_parallel_tree_l
earner.cpp:1:
C:/boost/boost-build/include/boost-1_63/boost/system/error_code.hpp:221:36: warn
ing: 'boost::system::posix_category' defined but not used [-Wunused-variable]
    static const error_category & posix_category = generic_category();
                                ^
C:/boost/boost-build/include/boost-1_63/boost/system/error_code.hpp:222:36: warn
ing: 'boost::system::errno_ecat' defined but not used [-Wunused-variable]
    static const error_category & errno_ecat = generic_category();
                                ^
C:/boost/boost-build/include/boost-1_63/boost/system/error_code.hpp:223:36: warn
ing: 'boost::system::native_ecat' defined but not used [-Wunused-variable]
    static const error_category & native_ecat = system_category();
                                ^
cc1plus.exe: warning: unrecognized command line option '-Wno-ignored-attributes'
[100%] Linking CXX shared library ..\lib_lightgbm.dll
[100%] Built target _lightgbm

Laurae@Laurae-Pro MINGW64 /c/xgboost/LightGBM/build (master)
$ |

```

If everything was done correctly, you now compiled CLI LightGBM with GPU support!

Testing in CLI

You can now test LightGBM directly in CLI in a **command prompt** (not Git Bash):

```
cd C:/github_repos/LightGBM/examples/binary_classification
"../../lightgbm.exe" config=train.conf data=binary.train valid=binary.test_
↪objective=binary device=gpu
```

```

Administrator: Command Prompt
C:\xgboost\LightGBM\examples\binary_classification>\".
[LightGBM] [Info] Finished loading parameters
[LightGBM] [Info] Loading weights...
[LightGBM] [Info] Loading weights...
[LightGBM] [Info] Finished loading data in 0.001050 seconds
[LightGBM] [Info] Number of positive: 3716, number of negative: 3284
[LightGBM] [Info] This is the GPU trainer!!
[LightGBM] [Info] Total Bins 6143
[LightGBM] [Info] Number of data: 7000, number of used features: 28
[LightGBM] [Info] Using GPU Device: Oland, Vendor: Advanced Micro Devices, Inc.
[LightGBM] [Info] Compiling OpenGL Kernel with 256 bins...
[LightGBM] [Info] GPU programs have been built
[LightGBM] [Info] Size of histogram bin entry: 12
[LightGBM] [Info] 28 dense feature groups (0.19 MB) transferred to GPU in 0.006987 secs. 0 sparse feature groups.
[LightGBM] [Info] Finished initializing training
[LightGBM] [Info] Started training...
[LightGBM] [Info] Size of histogram bin entry: 12
[LightGBM] [Info] 28 dense feature groups (0.15 MB) transferred to GPU in 0.001380 secs. 0 sparse feature groups.
[LightGBM] [Info] Trained a tree with leaves=63 and max_depth=10
[LightGBM] [Info] Iteration:1, training auc : 0.708052
[LightGBM] [Info] Iteration:1, training binary_logloss : 0.66901
[LightGBM] [Info] Iteration:1, valid_1 auc : 0.768882
[LightGBM] [Info] Iteration:1, valid_1 binary_logloss : 0.670815
[LightGBM] [Info] 0.074870 seconds elapsed, finished iteration 1
[LightGBM] [Info] Trained a tree with leaves=63 and max_depth=10

```

Congratulations for reaching this stage!

To learn how to target a correct CPU or GPU for training, please see: [GPU SDK Correspondence and Device Targeting Table](#).

17.1.9 Debugging LightGBM Crashes in CLI

Now that you compiled LightGBM, you try it... and you always see a segmentation fault or an undocumented crash with GPU support:

```

[New Thread 105220.0x19490]
[New Thread 105220.0x1a71c]
[New Thread 105220.0x19a24]
[New Thread 105220.0x4fb0]
[Thread 105220.0x4fb0 exited with code 0]
[LightGBM] [Info] Loading weights...
[New Thread 105220.0x19988]
[Thread 105220.0x19988 exited with code 0]
[New Thread 105220.0x1a8fc]
[Thread 105220.0x1a8fc exited with code 0]
[LightGBM] [Info] Loading weights...
[New Thread 105220.0x1a90c]
[Thread 105220.0x1a90c exited with code 0]
[LightGBM] [Info] Finished loading data in 1.011408 seconds
[LightGBM] [Info] Number of positive: 3716, number of negative: 3284
[LightGBM] [Info] This is the GPU trainer!!
[LightGBM] [Info] Total Bins 6143
[LightGBM] [Info] Number of data: 7000, number of used features: 28
[New Thread 105220.0x1a62c]
[LightGBM] [Info] Using GPU Device: Oland, Vendor: Advanced Micro Devices, Inc.
[LightGBM] [Info] Compiling OpenGL Kernel with 256 bins...
Program received signal SIGSEGV, Segmentation fault.
0x000007fbb37c11f1 in strlen (<) from C:\Windows\system32\msvcrt.dll
(adhb)

```

Please check if you are using the right device (Using GPU device: ...). You can find a list of your OpenCL devices using [GPUCapsViewer](#), and make sure you are using a discrete (AMD/NVIDIA) GPU if you have both integrated (Intel) and discrete GPUs installed. Also, try to set `gpu_device_id = 0` and `gpu_platform_id = 0` or `gpu_device_id = -1` and `gpu_platform_id = -1` to use the first platform and device or the default platform and device. If it still does not work, then you should follow all the steps below.

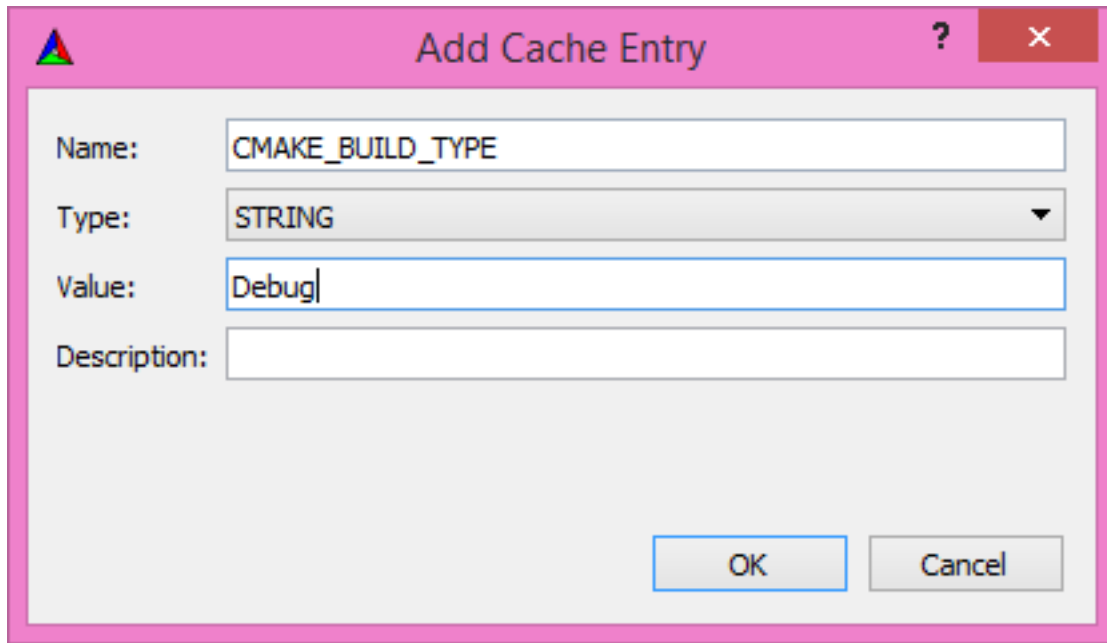
You will have to redo the compilation steps for LightGBM to add debugging mode. This involves:

- Deleting C:/github_repos/LightGBM/build folder
- Deleting `lightgbm.exe`, `lib_lightgbm.dll`, and `lib_lightgbm.dll.a` files

s PC > Local Disk (C:) > xgboost > LightGBM

| Name | Date modified | Type | Size |
|--------------------|----------------------|-----------------------|----------|
| .git | 13/04/2017 12:57 ... | File folder | |
| .github | 13/04/2017 12:57 ... | File folder | |
| .travis | 13/04/2017 12:57 ... | File folder | |
| build | 13/04/2017 09:33 ... | File folder | |
| compute | 13/04/2017 09:11 ... | File folder | |
| docker | 13/04/2017 12:57 ... | File folder | |
| docs | 13/04/2017 12:57 ... | File folder | |
| examples | 13/04/2017 12:57 ... | File folder | |
| include | 13/04/2017 12:57 ... | File folder | |
| pmml | 13/04/2017 12:57 ... | File folder | |
| python-package | 13/04/2017 12:57 ... | File folder | |
| R-package | 13/04/2017 12:57 ... | File folder | |
| src | 13/04/2017 12:57 ... | File folder | |
| tests | 13/04/2017 12:57 ... | File folder | |
| windows | 13/04/2017 12:57 ... | File folder | |
| .gitignore | 13/04/2017 12:57 ... | GITIGNORE File | 6 KB |
| .gitmodules | 13/04/2017 12:57 ... | Text Document | 1 KB |
| .travis.yml | 13/04/2017 12:57 ... | Visual Studio Code | 3 KB |
| CMakeLists.txt | 13/04/2017 12:57 ... | Text Document | 5 KB |
| lib_lightgbm.dll | 13/04/2017 09:36 ... | Application extens... | 2,377 KB |
| lib_lightgbm.dll.a | 13/04/2017 09:36 ... | A File | 1,775 KB |
| LICENSE | 13/04/2017 12:57 ... | File | 2 KB |
| lightgbm.exe | 13/04/2017 09:34 ... | Application | 2,139 KB |
| README.md | 13/04/2017 12:57 ... | Visual Studio Code | 5 KB |

Once you removed the file, go into CMake, and follow the usual steps. Before clicking “Generate”, click on “Add Entry”:

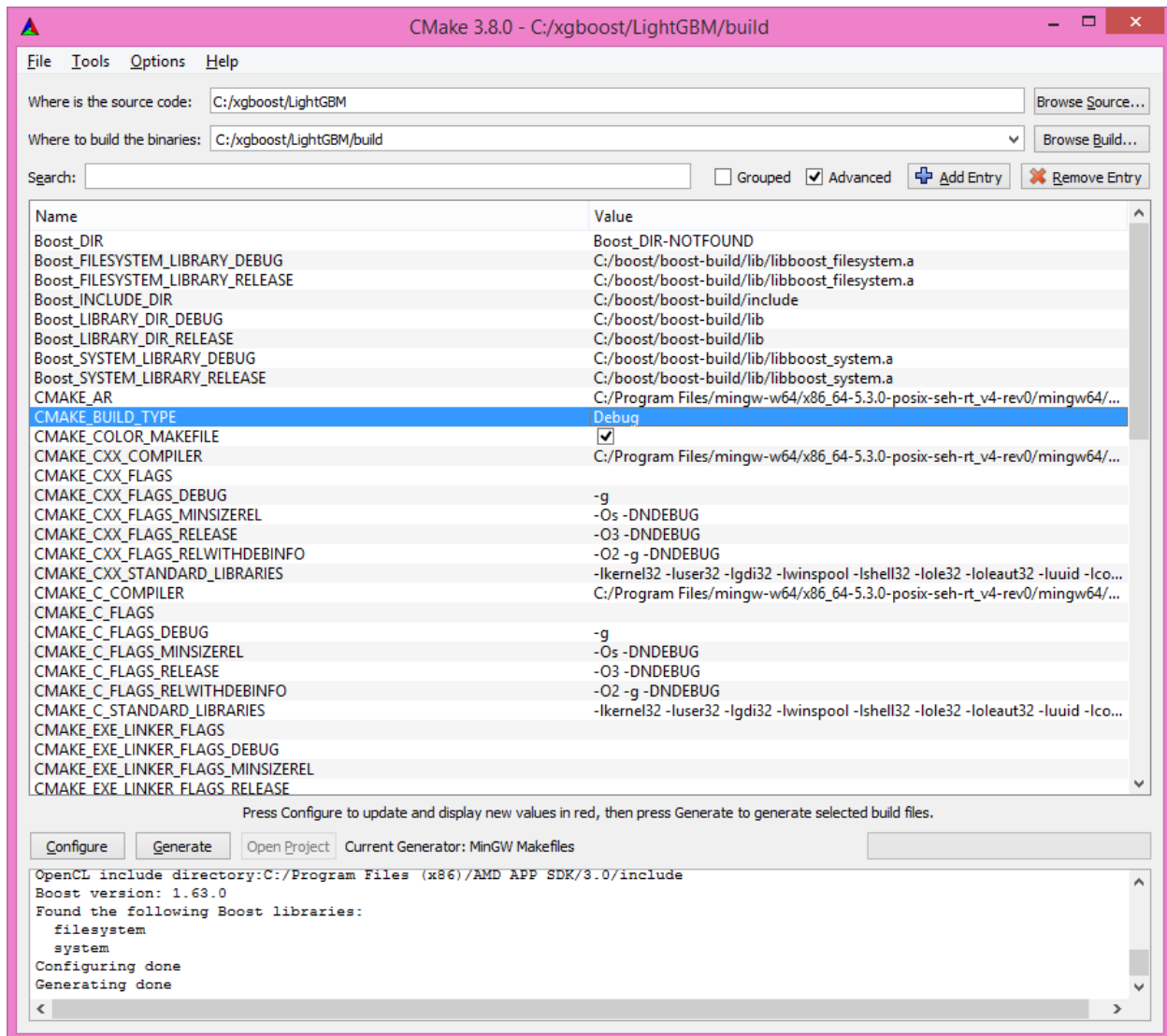


The image shows a dialog box titled "Add Cache Entry" with a pink border. It contains four input fields: "Name:" with the text "CMAKE_BUILD_TYPE", "Type:" with a dropdown menu showing "STRING", "Value:" with the text "Debug", and "Description:" which is empty. At the bottom right are "OK" and "Cancel" buttons.

| | |
|--------------|------------------|
| Name: | CMAKE_BUILD_TYPE |
| Type: | STRING |
| Value: | Debug |
| Description: | |

OK Cancel

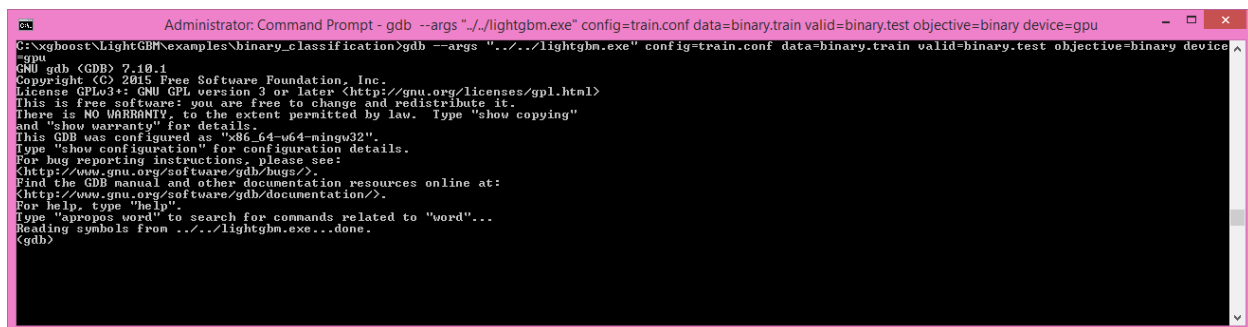
In addition, click on Configure and Generate:



And then, follow the regular LightGBM CLI installation from there.

Once you have installed LightGBM CLI, assuming your LightGBM is in `C:\github_repos\LightGBM`, open a command prompt and run the following:

```
gdb --args "../lightgbm.exe" config=train.conf data=binary.train valid=binary.test
↪objective=binary device=gpu
```



Type `run` and press the Enter key.

You will probably get something similar to this:

```
[LightGBM] [Info] This is the GPU trainer!!
[LightGBM] [Info] Total Bins 6143
[LightGBM] [Info] Number of data: 7000, number of used features: 28
[New Thread 105220.0x1a62c]
[LightGBM] [Info] Using GPU Device: Oland, Vendor: Advanced Micro Devices, Inc.
[LightGBM] [Info] Compiling OpenCL Kernel with 256 bins...

Program received signal SIGSEGV, Segmentation fault.
0x00007ffbb37c11f1 in strlen () from C:\Windows\system32\msvcrt.dll
(gdb)
```

There, write backtrace and press the Enter key as many times as gdb requests two choices:

```
Program received signal SIGSEGV, Segmentation fault.
0x00007ffbb37c11f1 in strlen () from C:\Windows\system32\msvcrt.dll
(gdb) backtrace
#0  0x00007ffbb37c11f1 in strlen () from C:\Windows\system32\msvcrt.dll
#1  0x000000000048bbe5 in std::char_traits<char>::length (__s=0x0)
    at C:/PROGRA~1/MINGW~1/X86_64-1.0-P/mingw64/x86_64-w64-mingw32/include/c++/bits/
    ↪char_traits.h:267
#2  std::operator+<char, std::char_traits<char>, std::allocator<char> > (__rhs="", _
    ↪_lhs=0x0)
    at C:/PROGRA~1/MINGW~1/X86_64-1.0-P/mingw64/x86_64-w64-mingw32/include/c++/bits/
    ↪basic_string.tcc:1157
#3  boost::compute::detail::appdata_path[abi:cxx11]() () at C:/boost/boost-build/
    ↪include/boost/compute/detail/path.hpp:38
#4  0x000000000048eec3 in boost::compute::detail::program_binary_path (hash=
    ↪"d27987d5bd61e2d28cd32b8d7a7916126354dc81", create=create@entry=false)
    at C:/boost/boost-build/include/boost/compute/detail/path.hpp:46
#5  0x00000000004913de in boost::compute::program::load_program_binary (hash=
    ↪"d27987d5bd61e2d28cd32b8d7a7916126354dc81", ctx=...)
    at C:/boost/boost-build/include/boost/compute/program.hpp:605
#6  0x0000000000490ece in boost::compute::program::build_with_source (
    source="\n#ifdef _HISTOGRAM_256_KERNEL_\n#define _HISTOGRAM_256_KERNEL_\n\n
    ↪#pragma OPENCL EXTENSION cl_khr_local_int32_base_atomics : enable\n#pragma OPENC
    L EXTENSION cl_khr_global_int32_base_atomics : enable\n\n/"..., context=...,
    options="-D POWER_FEATURE_WORKGROUPS=5 -D USE_CONSTANT_BUF=0 -D USE_DP_FLOAT=0 -
    ↪D CONST_HESSIAN=0 -cl-strict-aliasing -cl-mad-enable -cl-no-signed-zeros -c
    l-fast-relaxed-math") at C:/boost/boost-build/include/boost/compute/program.hpp:549
#7  0x0000000000454339 in LightGBM::GPUTreeLearner::BuildGPUKernels () at _
    ↪C:\LightGBM\src\treelearner\gpu_tree_learner.cpp:583
#8  0x0000000000636044f2 in libgomp-1\GOMP_parallel () from C:\Program Files\mingw-
    ↪w64\x86_64-5.3.0-posix-seh-rt_v4-rev0\mingw64\bin\libgomp-1.dll
#9  0x0000000000455e7e in LightGBM::GPUTreeLearner::BuildGPUKernels_
    ↪(this=this@entry=0x3b9cac0)
    at C:\LightGBM\src\treelearner\gpu_tree_learner.cpp:569
#10 0x0000000000457b49 in LightGBM::GPUTreeLearner::InitGPU (this=0x3b9cac0, platform_
    ↪id=<optimized out>, device_id=<optimized out>)
    at C:\LightGBM\src\treelearner\gpu_tree_learner.cpp:720
#11 0x0000000000410395 in LightGBM::GBDT::ResetTrainingData (this=0x1f26c90, config=
    ↪<optimized out>, train_data=0x1f28180, objective_function=0x1f280e0,
    training_metrics=std::vector of length 2, capacity 2 = {...}) at _
    ↪C:\LightGBM\src\boosting\gbdt.cpp:98
#12 0x0000000000402e93 in LightGBM::Application::InitTrain (this=this@entry=0x23f9d0) _
    ↪at C:\LightGBM\src\application\application.cpp:213
---Type <return> to continue, or q <return> to quit---
```

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```
#13 0x00000000004f0b55 in LightGBM::Application::Run (this=0x23f9d0) at C:/LightGBM/
↳include/LightGBM/application.h:84
#14 main (argc=6, argv=0x1f21e90) at C:/LightGBM/src/main.cpp:7
```

Right-click the command prompt, click “Mark”, and select all the text from the first line (with the command prompt containing gdb) to the last line printed, containing all the log, such as:

```
C:\LightGBM\examples\binary_classification>gdb --args "../..lightgbm.exe"
↳config=train.conf data=binary.train valid=binary.test objective=binary device=gpu
GNU gdb (GDB) 7.10.1
Copyright (C) 2015 Free Software Foundation, Inc.
License GPLv3+: GNU GPL version 3 or later <http://gnu.org/licenses/gpl.html>
This is free software: you are free to change and redistribute it.
There is NO WARRANTY, to the extent permitted by law. Type "show copying"
and "show warranty" for details.
This GDB was configured as "x86_64-w64-mingw32".
Type "show configuration" for configuration details.
For bug reporting instructions, please see:
<http://www.gnu.org/software/gdb/bugs/>.
Find the GDB manual and other documentation resources online at:
<http://www.gnu.org/software/gdb/documentation/>.
For help, type "help".
Type "apropos word" to search for commands related to "word"...
Reading symbols from ../..lightgbm.exe...done.
(gdb) run
Starting program: C:\LightGBM\lightgbm.exe "config=train.conf" "data=binary.train"
↳"valid=binary.test" "objective=binary" "device=gpu"
[New Thread 105220.0x199b8]
[New Thread 105220.0x783c]
[Thread 105220.0x783c exited with code 0]
[LightGBM] [Info] Finished loading parameters
[New Thread 105220.0x19490]
[New Thread 105220.0x1a71c]
[New Thread 105220.0x19a24]
[New Thread 105220.0x4fb0]
[Thread 105220.0x4fb0 exited with code 0]
[LightGBM] [Info] Loading weights...
[New Thread 105220.0x19988]
[Thread 105220.0x19988 exited with code 0]
[New Thread 105220.0x1a8fc]
[Thread 105220.0x1a8fc exited with code 0]
[LightGBM] [Info] Loading weights...
[New Thread 105220.0x1a90c]
[Thread 105220.0x1a90c exited with code 0]
[LightGBM] [Info] Finished loading data in 1.011408 seconds
[LightGBM] [Info] Number of positive: 3716, number of negative: 3284
[LightGBM] [Info] This is the GPU trainer!!
[LightGBM] [Info] Total Bins 6143
[LightGBM] [Info] Number of data: 7000, number of used features: 28
[New Thread 105220.0x1a62c]
[LightGBM] [Info] Using GPU Device: Oland, Vendor: Advanced Micro Devices, Inc.
[LightGBM] [Info] Compiling OpenCL Kernel with 256 bins...

Program received signal SIGSEGV, Segmentation fault.
0x00007ffbb37c11f1 in strlen () from C:\Windows\system32\msvcrt.dll
(gdb) backtrace
```

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```

#0 0x00007ffbb37c11f1 in strlen () from C:\Windows\system32\msvcrt.dll
#1 0x00000000048bbe5 in std::char_traits<char>::length (__s=0x0)
    at C:/PROGRA~1/MINGW~1/X86_64~1.0-P/mingw64/x86_64-w64-mingw32/include/c++/bits/
    ↪char_traits.h:267
#2 std::operator+<char, std::char_traits<char>, std::allocator<char> > (__rhs="", _
    ↪_lhs=0x0)
    at C:/PROGRA~1/MINGW~1/X86_64~1.0-P/mingw64/x86_64-w64-mingw32/include/c++/bits/
    ↪basic_string.tcc:1157
#3 boost::compute::detail::appdata_path[abi:cxx11]() () at C:/boost/boost-build/
    ↪include/boost/compute/detail/path.hpp:38
#4 0x00000000048eec3 in boost::compute::detail::program_binary_path (hash=
    ↪"d27987d5bd61e2d28cd32b8d7a7916126354dc81", create=create@entry=false)
    at C:/boost/boost-build/include/boost/compute/detail/path.hpp:46
#5 0x0000000004913de in boost::compute::program::load_program_binary (hash=
    ↪"d27987d5bd61e2d28cd32b8d7a7916126354dc81", ctx=...)
    at C:/boost/boost-build/include/boost/compute/program.hpp:605
#6 0x000000000490ece in boost::compute::program::build_with_source (
    source="\n#ifdef _HISTOGRAM_256_KERNEL_\n#define _HISTOGRAM_256_KERNEL_\n\n
    ↪#pragma OPENCL EXTENSION cl_khr_local_int32_base_atomics : enable\n#pragma OPENCL
    ↪EXTENSION cl_khr_global_int32_base_atomics : enable\n\n/"..., context=...,
    options="-D POWER_FEATURE_WORKGROUPS=5 -D USE_CONSTANT_BUF=0 -D USE_DP_FLOAT=0 -
    ↪D CONST_HESSIAN=0 -cl-strict-aliasing -cl-mad-enable -cl-no-signed-zeros -cl-fast-
    ↪relaxed-math") at C:/boost/boost-build/include/boost/compute/program.hpp:549
#7 0x000000000454339 in LightGBM::GPULearner::BuildGPUKernels () at
    ↪C:\LightGBM\src\treelearner\gpu_tree_learner.cpp:583
#8 0x00000000636044f2 in libgomp-1!GOMP_parallel () from C:\Program Files\mingw-
    ↪w64\x86_64-5.3.0-posix-seh-rt_v4-rev0\mingw64\bin\libgomp-1.dll
#9 0x000000000455e7e in LightGBM::GPULearner::BuildGPUKernels
    ↪(this=this@entry=0x3b9cac0)
    at C:\LightGBM\src\treelearner\gpu_tree_learner.cpp:569
#10 0x000000000457b49 in LightGBM::GPULearner::InitGPU (this=0x3b9cac0, platform_
    ↪id=<optimized out>, device_id=<optimized out>)
    at C:\LightGBM\src\treelearner\gpu_tree_learner.cpp:720
#11 0x000000000410395 in LightGBM::GBDT::ResetTrainingData (this=0x1f26c90, config=
    ↪<optimized out>, train_data=0x1f28180, objective_function=0x1f280e0,
    training_metrics=std::vector of length 2, capacity 2 = {...}) at
    ↪C:\LightGBM\src\boosting\gbdt.cpp:98
#12 0x000000000402e93 in LightGBM::Application::InitTrain (this=this@entry=0x23f9d0)
    ↪at C:\LightGBM\src\application\application.cpp:213
---Type <return> to continue, or q <return> to quit---
#13 0x0000000004f0b55 in LightGBM::Application::Run (this=0x23f9d0) at C:/LightGBM/
    ↪include/LightGBM/application.h:84
#14 main (argc=6, argv=0x1f21e90) at C:\LightGBM\src\main.cpp:7

```

And open an issue in GitHub [here](#) with that log.

Recommendations When Using gcc

It is recommended to use `-O3 -mtune=native` to achieve maximum speed during LightGBM training.

Using Intel Ivy Bridge CPU on 1M x 1K Bosch dataset, the performance increases as follow:

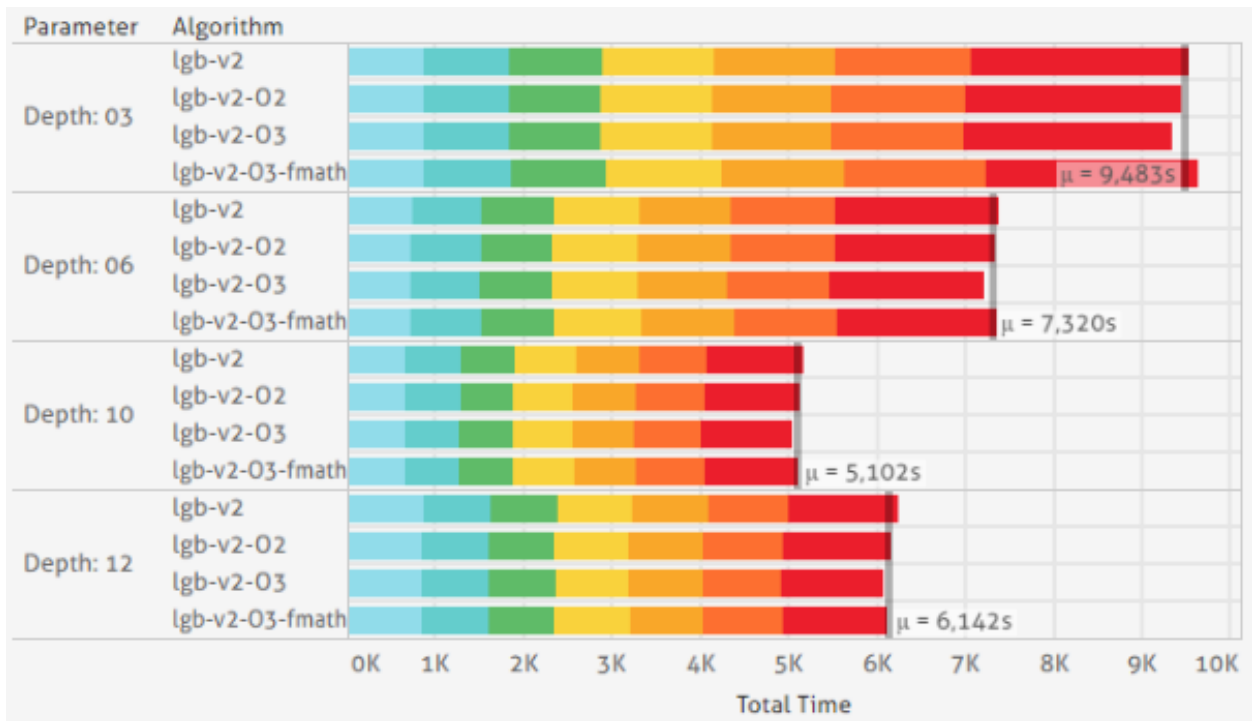
| Compilation Flag | Performance Index |
|--|-------------------|
| <code>-O2 -mtune=core2</code> | 100.00% |
| <code>-O2 -mtune=native</code> | 100.90% |
| <code>-O3 -mtune=native</code> | 102.78% |
| <code>-O3 -ffast-math -mtune=native</code> | 100.64% |

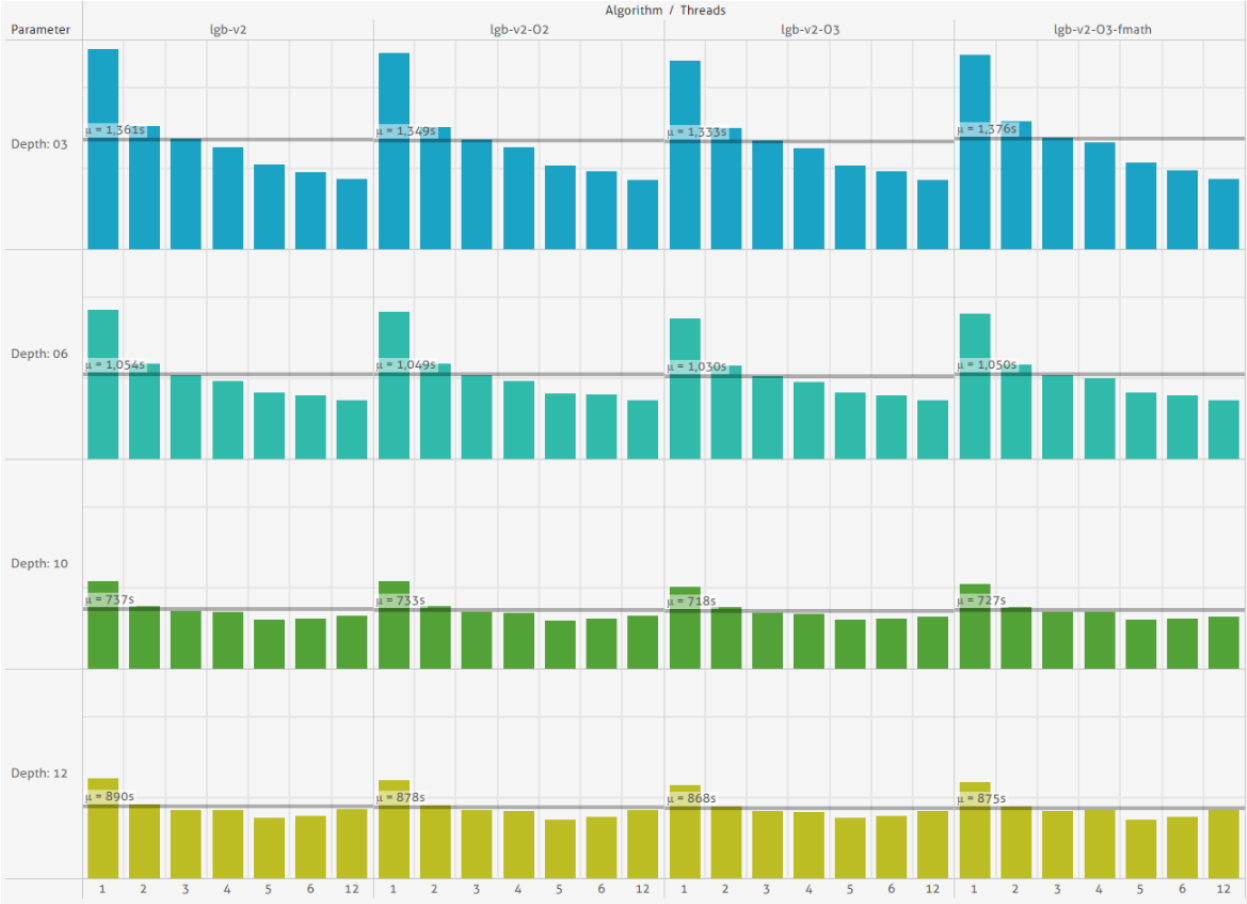
You can find more details on the experimentation below:

- [Laurae++/Benchmarks](#)
- [Laurae2/gbt_benchmarks](#)
- [Laurae's Benchmark Master Data \(Interactive\)](#)
- [Kaggle Paris Meetup #12 Slides](#)

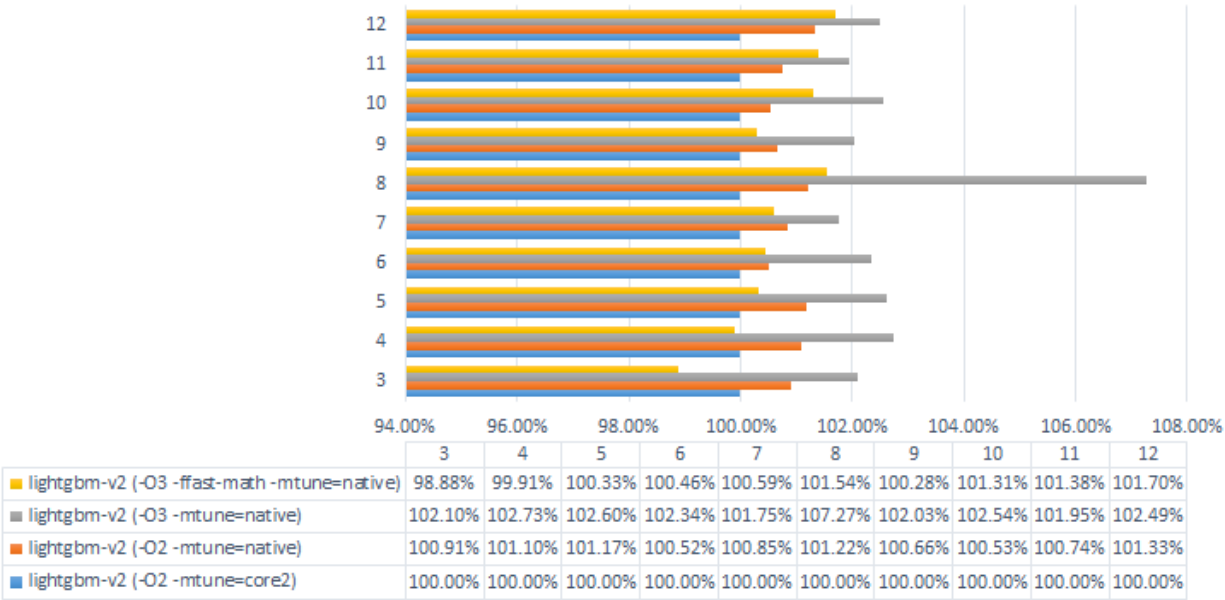
Some explanatory pictures:

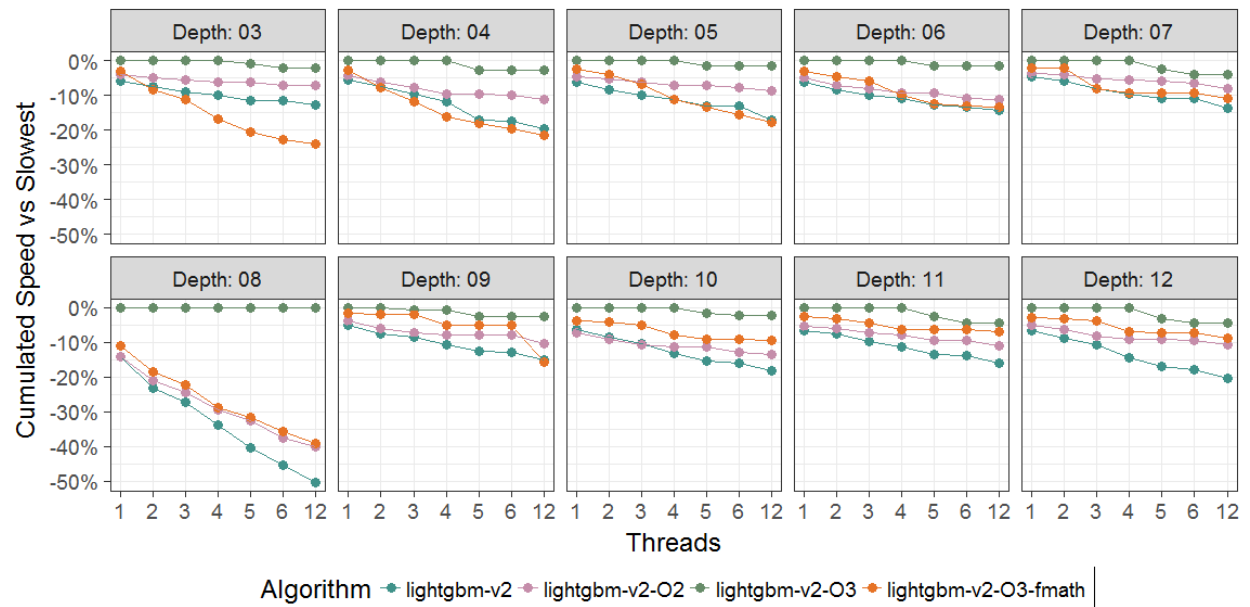
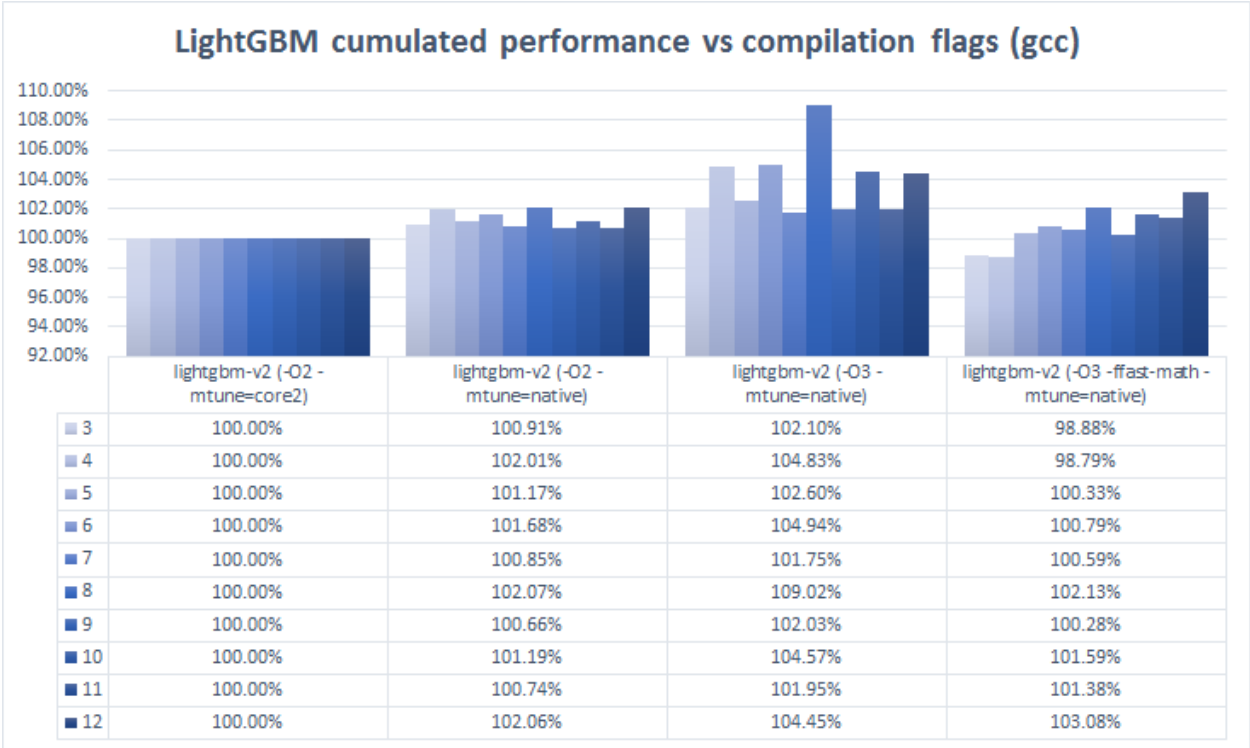
| Parameter | Algorithm | Threads | | | | | | | Total |
|-----------|-----------------|---------|-------|-------|-------|-------|-----|-----|-------|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 12 | |
| Depth: 03 | lgb-v2 | 2,477 | 1,533 | 1,370 | 1,267 | 1,051 | 956 | 873 | 9,528 |
| | lgb-v2-02 | 2,438 | 1,521 | 1,358 | 1,261 | 1,035 | 965 | 862 | 9,440 |
| | lgb-v2-03 | 2,343 | 1,509 | 1,349 | 1,254 | 1,042 | 970 | 862 | 9,328 |
| | lgb-v2-03-fmath | 2,412 | 1,588 | 1,390 | 1,321 | 1,076 | 976 | 872 | 9,634 |
| Depth: 06 | lgb-v2 | 1,851 | 1,183 | 1,039 | 970 | 821 | 788 | 730 | 7,381 |
| | lgb-v2-02 | 1,830 | 1,180 | 1,035 | 971 | 807 | 795 | 725 | 7,343 |
| | lgb-v2-03 | 1,745 | 1,155 | 1,025 | 959 | 819 | 783 | 723 | 7,208 |
| | lgb-v2-03-fmath | 1,799 | 1,173 | 1,038 | 997 | 827 | 788 | 725 | 7,347 |
| Depth: 10 | lgb-v2 | 1,083 | 774 | 712 | 703 | 608 | 621 | 659 | 5,159 |
| | lgb-v2-02 | 1,091 | 772 | 708 | 689 | 595 | 625 | 651 | 5,132 |
| | lgb-v2-03 | 1,017 | 759 | 697 | 685 | 605 | 619 | 646 | 5,028 |
| | lgb-v2-03-fmath | 1,055 | 762 | 704 | 704 | 603 | 616 | 647 | 5,091 |
| Depth: 12 | lgb-v2 | 1,237 | 913 | 851 | 853 | 749 | 770 | 855 | 6,228 |
| | lgb-v2-02 | 1,216 | 907 | 850 | 830 | 730 | 766 | 845 | 6,146 |
| | lgb-v2-03 | 1,159 | 894 | 835 | 824 | 753 | 773 | 835 | 6,073 |
| | lgb-v2-03-fmath | 1,191 | 898 | 839 | 850 | 734 | 763 | 847 | 6,122 |

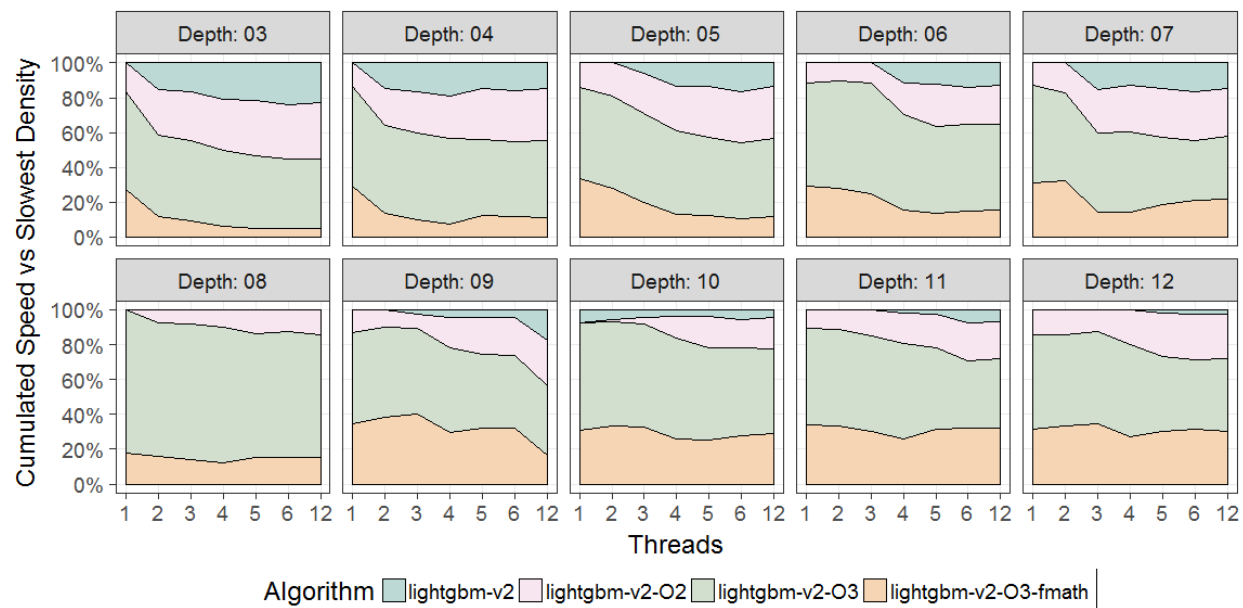




LightGBM performance vs compilation flags (gcc)







CHAPTER 19

Documentation

Documentation for LightGBM is generated using [Sphinx](#) and [Breathe](#), which works on top of [Doxygen](#) output.

List of parameters and their descriptions in [Parameters.rst](#) is generated automatically from comments in [config file](#) by [this script](#).

After each commit on `master`, documentation is updated and published to [Read the Docs](#).

19.1 Build

You can build the documentation locally. Just install Doxygen and run in `docs` folder

```
pip install -r requirements.txt
make html
```

Unfortunately, documentation for R code is built only on our site, and commands above will not build it for you locally. Consider using common R utilities for documentation generation, if you need it.

If you faced any problems with Doxygen installation or you simply do not need documentation for C code, it is possible to build the documentation without it:

```
pip install -r requirements_base.txt
export C_API=NO || set C_API=NO
make html
```


CHAPTER 20

Indices and Tables

- `genindex`

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