



LightGBM

Release 3.3.1.99

Microsoft Corporation

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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, distributed, and GPU learning.
- Capable of handling large-scale data.

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

INSTALLATION GUIDE

This is a guide for building the LightGBM Command Line Interface (CLI). If you want to build the Python-package or R-package please refer to [Python-package](#) and [R-package](#) folders respectively.

All instructions below are aimed at compiling the 64-bit version of LightGBM. It is worth compiling the 32-bit version only in very rare special cases involving environmental limitations. The 32-bit version is slow and untested, so use it at your own risk and don't forget to adjust some of the commands below when installing.

If you need to build a static library instead of a shared one, you can add `-DBUILD_STATIC_LIB=ON` to CMake flags.

Users who want to perform benchmarking can make LightGBM output time costs for different internal routines by adding `-DUSE_TIMETAG=ON` to CMake flags.

It is possible to build LightGBM in debug mode. In this mode all compiler optimizations are disabled and LightGBM performs more checks internally. To enable debug mode you can add `-DUSE_DEBUG=ON` to CMake flags or choose `Debug_*` configuration (e.g. `Debug_DLL`, `Debug_mpi`) in Visual Studio depending on how you are building LightGBM.

In addition to the debug mode, LightGBM can be built with compiler sanitizers. To enable them add `-DUSE_SANITIZER=ON` `-DENABLED_SANITIZERS="address;leak;undefined"` to CMake flags. These values refer to the following supported sanitizers:

- `address` - AddressSanitizer (ASan);
- `leak` - LeakSanitizer (LSan);
- `undefined` - UndefinedBehaviorSanitizer (UBSan);
- `thread` - ThreadSanitizer (TSan).

Please note, that ThreadSanitizer cannot be used together with other sanitizers. For more info and additional sanitizers' parameters please refer to the [following docs](#). It is very useful to build *C++ unit tests* with sanitizers.

You can also download the artifacts of the latest successful build on master branch (nightly builds) here: .

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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 that you use **Visual Studio** since it has 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.

Note: In some rare cases you may need to install OpenMP runtime library separately (use your package manager and search for `lib[g|i]omp` for doing this).

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** (3.16 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
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. You can build LightGBM without OpenMP support but it is **strongly not recommended**.

1.5.1 Windows

On Windows a 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
```

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```
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 a 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 a 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** (3.16 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 distributed learning application with high performance communication, you can build the LightGBM with MPI support.

1.6.1 Windows

On Windows an 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 `msmpisdsk.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 `msmpisdsk.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 an 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.

Note: In some rare cases you may need to install OpenMP runtime library separately (use your package manager and search for lib[g|i]omp for doing this).

1.6.3 macOS

On macOS an 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** (3.16 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
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 a GPU version of LightGBM (`device_type=gpu`) 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
```

Note: glibc >= 2.14 is required.

Note: In some rare cases you may need to install OpenMP runtime library separately (use your package manager and search for `lib[g|i]omp` for doing this).

1.7.2 Windows

On Windows a GPU version of LightGBM (`device_type=gpu`) 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`,

Visual Studio 2022 -> `msvc-14.3-64.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 CUDA Version (Experimental)

The *original GPU build* of LightGBM (`device_type=gpu`) is based on OpenCL.

The CUDA-based build (`device_type=cuda`) is a separate implementation and requires an NVIDIA graphics card with compute capability 6.0 and higher. It should be considered experimental, and we suggest using it only when it is impossible to use OpenCL version (for example, on IBM POWER microprocessors).

Note: only Linux is supported, other operating systems are not supported yet.

1.8.1 Linux

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

The following dependencies should be installed before compilation:

- **CUDA** 9.0 or later libraries. Please refer to [this detailed guide](#). Pay great attention to the minimum required versions of host compilers listed in the table from that guide and use only recommended versions of compilers.
- **CMake** 3.16 or later.

To build LightGBM CUDA version, run the following commands:

```
git clone --recursive https://github.com/microsoft/LightGBM
cd LightGBM
mkdir build
cd build
cmake -DUSE_CUDA=1 ..
make -j4
```

Note: glibc >= 2.14 is required.

Note: In some rare cases you may need to install OpenMP runtime library separately (use your package manager and search for `lib[g|i]omp` for doing this).

1.9 Build HDFS Version

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

1.9.1 Linux

On Linux a 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
```

Note: glibc >= 2.14 is required.

Note: In some rare cases you may need to install OpenMP runtime library separately (use your package manager and search for lib[g|i]omp for doing this).

1.10 Build Java Wrapper

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

1.10.1 Windows

On Windows a 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)** since it has better multithreading efficiency in **Windows** for many-core systems (see [Question 4](#) and [Question 8](#)).

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

1.10.2 Linux

On Linux a 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
```

Note: `glibc >= 2.14` is required.

Note: In some rare cases you may need to install OpenMP runtime library separately (use your package manager and search for `lib[g|i]omp` for doing this).

1.10.3 macOS

On macOS a 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** (3.16 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
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](#).

1.11 Build C++ Unit Tests

1.11.1 Windows

On Windows, C++ unit tests of LightGBM can be built using **CMake** and **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. Run the following commands:

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

The .exe file will be in LightGBM/Debug folder.

1.11.2 Linux

On Linux a C++ unit tests of 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 -DBUILD_CPP_TEST=ON -DUSE_OPENMP=OFF ..
make testlightgbm -j4
```

Note: glibc >= 2.14 is required.

1.11.3 macOS

On macOS a C++ unit tests of LightGBM 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** (3.16 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 -DBUILD_CPP_TEST=ON -DUSE_OPENMP=OFF ..
make testlightgbm -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 -DBUILD_CPP_TEST=ON -DUSE_OPENMP=OFF ..
make testlightgbm -j4
```


QUICK START

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](#)
- [Distributed Learning](#)

PYTHON-PACKAGE INTRODUCTION

This document gives a basic walk-through of LightGBM Python-package.

List of other helpful links

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

3.1 Install

The preferred way to install LightGBM is via pip:

```
pip install lightgbm
```

Refer to [Python-package](#) folder for the detailed 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 format text file
- NumPy 2D array(s), pandas DataFrame, H2O DataTable's Frame, SciPy sparse matrix
- LightGBM binary file
- LightGBM Sequence object(s)

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((dat, (row, col)))
train_data = lgb.Dataset(csr)
```

Load from Sequence objects:

We can implement Sequence interface to read binary files. The following example shows reading HDF5 file with h5py.

```
import h5py

class HDFSequence(lgb.Sequence):
    def __init__(self, hdf_dataset, batch_size):
        self.data = hdf_dataset
        self.batch_size = batch_size

    def __getitem__(self, idx):
        return self.data[idx]

    def __len__(self):
        return len(self.data)

f = h5py.File('train.hdf5', 'r')
train_data = lgb.Dataset(HDFSequence(f['X'], 8192), label=f['Y'][:])
```

Features of using Sequence interface:

- Data sampling uses random access, thus does not go through the whole dataset
- Reading data in batch, thus saves memory when constructing Dataset object
- Supports creating Dataset from multiple data files

Please refer to Sequence [API doc](#).

`dataset_from_multi_hdf5.py` is a detailed example.

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 encoding, and is much faster than one-hot encoding (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, callbacks=[lgb.
↳early_stopping(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 `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` callback. 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 `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)
```


FEATURES

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 distributed learning**

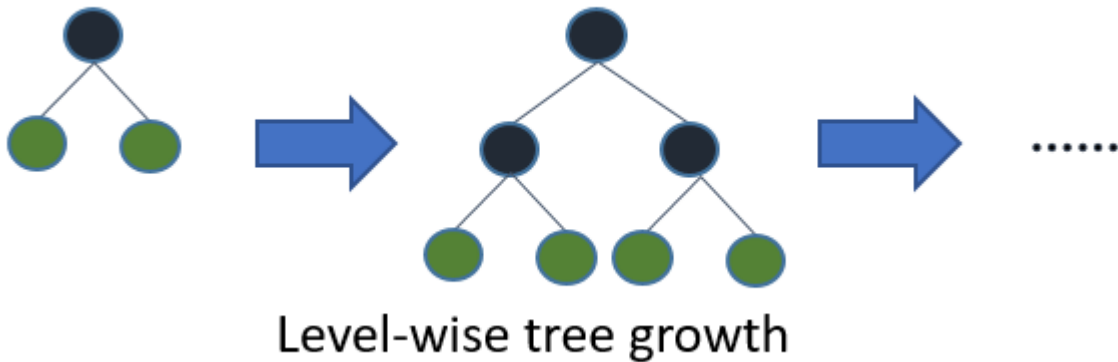
4.2 Sparse Optimization

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

4.3 Optimization in Accuracy

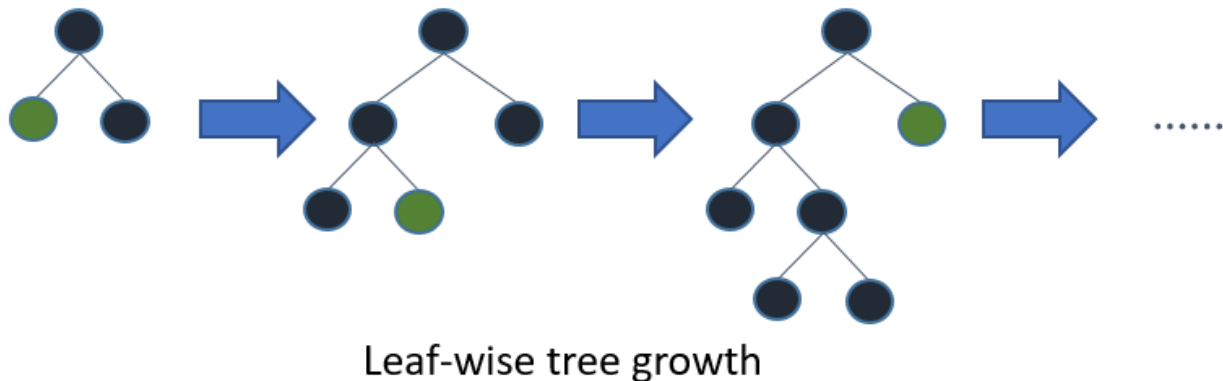
4.3.1 Leaf-wise (Best-first) Tree Growth

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 distributed 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 Distributed Learning

LightGBM provides the following distributed 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
- AUC-mu (new in v3.0.0)
- Average precision (new in v3.1.0)
- 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.
- [2] Mehta, Manish, Rakesh Agrawal, and Jorma Rissanen. “SLIQ: A fast scalable classifier for data mining.” International Conference on Extending Database Technology. Springer Berlin Heidelberg, 1996.
- [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.

EXPERIMENTS

5.1 Comparison Experiment

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

5.1.1 History

08 Mar, 2020: update according to the latest master branch ([1b97eaf](#) for XGBoost, [bcad692](#) for LightGBM). (xgboost_exact is not updated for it is too slow.)

27 Feb, 2017: first version.

5.1.2 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

5.1.3 Environment

We ran all experiments on a single Linux server (Azure ND24s) with the following specifications:

OS	CPU	Memory
Ubuntu 16.04 LTS	2 * E5-2690 v4	448GB

5.1.4 Baseline

We used `xgboost` as a baseline.

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

5.1.5 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
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.

5.1.6 Result

Speed

We compared speed using only the training task without any test or metric output. We didn't count the time for IO. For the ranking tasks, since XGBoost and LightGBM implement different ranking objective functions, we used regression objective for speed benchmark, for the fair comparison.

The following table is the comparison of time cost:

Data	xgboost	xgboost_hist	LightGBM
Higgs	3794.34 s	165.575 s	130.094 s
Yahoo LTR	674.322 s	131.462 s	76.229 s
MS LTR	1251.27 s	98.386 s	70.417 s
Expo	1607.35 s	137.65 s	62.607 s
Allstate	2867.22 s	315.256 s	148.231 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	0.845314	0.845724
Yahoo LTR	NDCG ₁	0.719748	0.720049	0.732981
	NDCG ₃	0.717813	0.722573	0.735689
	NDCG ₅	0.737849	0.740899	0.75352
	NDCG ₁₀	0.78089	0.782957	0.793498
MS LTR	NDCG ₁	0.483956	0.485115	0.517767
	NDCG ₃	0.467951	0.47313	0.501063
	NDCG ₅	0.472476	0.476375	0.504648
	NDCG ₁₀	0.492429	0.496553	0.524252
Expo	AUC	0.756713	0.776224	0.776935
Allstate	AUC	0.607201	0.609465	0.609072

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 (col-wise)	LightGBM (row-wise)
Higgs	4.853GB	7.335GB	0.897GB	1.401GB
Yahoo LTR	1.907GB	4.023GB	1.741GB	2.161GB
MS LTR	5.469GB	7.491GB	0.940GB	1.296GB
Expo	1.553GB	2.606GB	0.555GB	0.711GB
Allstate	6.237GB	12.090GB	1.116GB	1.755GB

5.2 Parallel Experiment

5.2.1 History

27 Feb, 2017: first version.

5.2.2 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 click-through 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.

5.2.3 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

5.2.4 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.

5.2.5 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 distributed learning.

5.3 GPU Experiments

Refer to [GPU Performance](#).

PARAMETERS

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.

For the Python and R packages, any parameters that accept a list of values (usually they have `multi-xxx` type, e.g. `multi-int` or `multi-double`) can be specified in those languages' default array types. For example, `monotone_constraints` can be specified as follows.

Python

```
params = {  
    "monotone_constraints": [-1, 0, 1]  
}
```

R

```
params <- list(  
  monotone_constraints = c(-1, 0, 1)  
)
```

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 [Convert Parameters](#)
 - `refit`, for refitting existing models with new data, aliases: `refit_tree`
 - `save_binary`, load train (and validation) data then save dataset to binary file. Typical usage: `save_binary` first, then run multiple `train` tasks in parallel using the saved binary file
 - **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`, `lamdarank`, `rank_xendcg`, aliases: `objective_type`, `app`, `application`, `loss`
 - 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 classification application
 - * `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 $[0, 1]$
- ranking application
 - * `lambdarank`, `lambdarank` objective. `label_gain` can be used to set the gain (weight) of `int` label and all values in `label` must be smaller than number of elements in `label_gain`
 - * `rank_xendcg`, `XE_NDCG_MART` ranking objective function, aliases: `xendcg`, `xe_ndcg`, `xe_ndcg_mart`, `xendcg_mart`
 - * `rank_xendcg` is faster than and achieves the similar performance as `lambdarank`
 - * label should be `int` type, and larger number represents the higher relevance (e.g. 0:bad, 1:fair, 2:good, 3:perfect)
- `boosting`, default = `gbdt`, type = enum, options: `gbdt`, `rf`, `dart`, `goss`, aliases: `boosting_type`, `boost`
 - `gbdt`, traditional Gradient Boosting Decision Tree, aliases: `gbdt`
 - `rf`, Random Forest, aliases: `random_forest`
 - `dart`, [Dropouts meet Multiple Additive Regression Trees](#)
 - `goss`, Gradient-based One-Side Sampling
 - * **Note:** internally, LightGBM uses `gbdt` mode for the first $1 / \text{learning_rate}$ iterations
- `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`, `nrounds`, `num_boost_round`, `n_estimators`, `max_iter`, 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`, `max_leaf_nodes`, 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 [Distributed Learning Guide](#) to get more details
- `num_threads` , default = `0`, type = int, aliases: `num_thread`, `nthread`, `nthreads`, `n_jobs`
 - used only in `train`, `prediction` and `refit` tasks or in correspondent functions of language-specific packages
 - 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 distributed learning, do not use all CPU cores because this will cause poor performance for the network communication
 - **Note:** please **don't** change this during training, especially when running multiple jobs simultaneously by external packages, otherwise it may cause undesirable errors
- `device_type` , default = `cpu`, type = enum, options: `cpu`, `gpu`, `cuda`, 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
- `deterministic` , default = `false`, type = bool
 - used only with `cpu` device type
 - setting this to `true` should ensure the stable results when using the same data and the same parameters (and different `num_threads`)
 - when you use the different seeds, different LightGBM versions, the binaries compiled by different compilers, or in different systems, the results are expected to be different

- you can [raise issues](#) in LightGBM GitHub repo when you meet the unstable results
- **Note:** setting this to `true` may slow down the training
- **Note:** to avoid potential instability due to numerical issues, please set `force_col_wise=true` or `force_row_wise=true` when setting `deterministic=true`

6.3 Learning Control Parameters

- `force_col_wise` , default = `false`, type = `bool`
 - used only with `cpu` device type
 - set this to `true` to force col-wise histogram building
 - enabling this is recommended when:
 - * the number of columns is large, or the total number of bins is large
 - * `num_threads` is large, e.g. `> 20`
 - * you want to reduce memory cost
 - **Note:** when both `force_col_wise` and `force_row_wise` are `false`, LightGBM will firstly try them both, and then use the faster one. To remove the overhead of testing set the faster one to `true` manually
 - **Note:** this parameter cannot be used at the same time with `force_row_wise`, choose only one of them
- `force_row_wise` , default = `false`, type = `bool`
 - used only with `cpu` device type
 - set this to `true` to force row-wise histogram building
 - enabling this is recommended when:
 - * the number of data points is large, and the total number of bins is relatively small
 - * `num_threads` is relatively small, e.g. `<= 16`
 - * you want to use small `bagging_fraction` or `goss` boosting to speed up
 - **Note:** setting this to `true` will double the memory cost for Dataset object. If you have not enough memory, you can try setting `force_col_wise=true`
 - **Note:** when both `force_col_wise` and `force_row_wise` are `false`, LightGBM will firstly try them both, and then use the faster one. To remove the overhead of testing set the faster one to `true` manually
 - **Note:** this parameter cannot be used at the same time with `force_col_wise`, choose only one of them
- `histogram_pool_size` , default = `-1.0`, type = `double`, aliases: `hist_pool_size`
 - max cache size in MB for historical histogram
 - `< 0` means no limit
- `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`, `min_samples_leaf`, constraints: `min_data_in_leaf >= 0`

- minimal number of data in one leaf. Can be used to deal with over-fitting
- **Note:** this is an approximation based on the Hessian, so occasionally you may observe splits which produce leaf nodes that have less than this many observations
- `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. Every k-th iteration, LightGBM will randomly select `bagging_fraction * 100` % of the data to use for the next k iterations
 - **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 a subset of features on each iteration (tree) if `feature_fraction` is 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 a subset of features on each tree node if `feature_fraction_bynode` is 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`
- `extra_trees` , default = false, type = bool, aliases: `extra_tree`
 - use extremely randomized trees
 - if set to true, when evaluating node splits LightGBM will check only one randomly-chosen threshold for each feature
 - can be used to speed up training
 - can be used to deal with over-fitting
- `extra_seed` , default = 6, type = int
 - random seed for selecting thresholds when `extra_trees` is true
- `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
 - can be used to speed up training
- `first_metric_only` , default = false, type = bool
 - LightGBM allows you to provide multiple evaluation metrics. 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`, `l1_regularization`, constraints: `lambda_l1 >= 0.0`
 - L1 regularization
- `lambda_l2` , default = `0.0`, type = double, aliases: `reg_lambda`, `lambda`, `l2_regularization`, constraints: `lambda_l2 >= 0.0`
 - L2 regularization
- `linear_lambda` , default = `0.0`, type = double, constraints: `linear_lambda >= 0.0`
 - linear tree regularization, corresponds to the parameter `lambda` in Eq. 3 of [Gradient Boosting with Piece-Wise Linear Regression Trees](#)
- `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
 - can be used to speed up training
- `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 <= top_rate <= 1.0`
 - used only in goss
 - the retain ratio of large gradient data
- `other_rate` , default = `0.1`, type = double, constraints: `0.0 <= other_rate <= 1.0`

- used only in goss
- the retain ratio of small gradient data
- `min_data_per_group` , default = 100, type = int, constraints: `min_data_per_group > 0`
 - minimal number of data per categorical group
- `max_cat_threshold` , default = 32, type = int, constraints: `max_cat_threshold > 0`
 - used for the categorical features
 - limit number of split points considered for categorical features. See [the documentation on how LightGBM finds optimal splits for categorical features](#) for more details
 - can be used to speed up training
- `cat_l2` , default = 10.0, type = double, constraints: `cat_l2 >= 0.0`
 - used for the categorical features
 - L2 regularization in categorical split
- `cat_smooth` , default = 10.0, type = double, constraints: `cat_smooth >= 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: `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: `top_k > 0`
 - used only in voting tree learner, refer to [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`, `monotonic_cst`
 - 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
- `monotone_constraints_method` , default = basic, type = enum, options: `basic`, `intermediate`, `advanced`, aliases: `monotone_constraining_method`, `mc_method`
 - used only if `monotone_constraints` is set
 - monotone constraints method
 - * `basic`, the most basic monotone constraints method. It does not slow the library at all, but over-constrains the predictions
 - * `intermediate`, a [more advanced method](#), which may slow the library very slightly. However, this method is much less constraining than the basic method and should significantly improve the results
 - * `advanced`, an [even more advanced method](#), which may slow the library. However, this method is even less constraining than the intermediate method and should again significantly improve the results
- `monotone_penalty` , default = 0.0, type = double, aliases: `monotone_splits_penalty`, `ms_penalty`, `mc_penalty`, constraints: `monotone_penalty >= 0.0`

- used only if `monotone_constraints` is set
- `monotone_penalty`: a penalization parameter X forbids any monotone splits on the first X (rounded down) level(s) of the tree. The penalty applied to monotone splits on a given depth is a continuous, increasing function the penalization parameter
- if `0.0` (the default), no penalization is applied
- `feature_contri` , default = `None`, type = multi-double, aliases: `feature_contrib`, `fc`, `fp`, `feature_penalty`
 - used to control feature's split gain, will use `gain[i] = max(0, feature_contri[i]) * 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
- `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
- `path_smooth` , default = `0`, type = double, constraints: `path_smooth >= 0.0`
 - controls smoothing applied to tree nodes
 - helps prevent overfitting on leaves with few samples
 - if set to zero, no smoothing is applied
 - if `path_smooth > 0` then `min_data_in_leaf` must be at least 2

- larger values give stronger regularization
 - * the weight of each node is $(n / \text{path_smooth}) * w + w_p / (n / \text{path_smooth} + 1)$, where n is the number of samples in the node, w is the optimal node weight to minimise the loss (approximately $-\text{sum_gradients} / \text{sum_hessians}$), and w_p is the weight of the parent node
 - * note that the parent output w_p itself has smoothing applied, unless it is the root node, so that the smoothing effect accumulates with the tree depth
- `interaction_constraints` , default = "", type = string
 - controls which features can appear in the same branch
 - by default interaction constraints are disabled, to enable them you can specify
 - * for CLI, lists separated by commas, e.g. `[0, 1, 2], [2, 3]`
 - * for Python-package, list of lists, e.g. `[[0, 1, 2], [2, 3]]`
 - * for R-package, list of character or numeric vectors, e.g. `list(c("var1", "var2", "var3"), c("var3", "var4"))` or `list(c(1L, 2L, 3L), c(3L, 4L))`. Numeric vectors should use 1-based indexing, where 1L is the first feature, 2L is the second feature, etc
 - any two features can only appear in the same branch only if there exists a constraint containing both features
- `verbosity` , default = 1, type = int, aliases: `verbose`
 - controls the level of LightGBM's verbosity
 - `< 0`: Fatal, `= 0`: Error (Warning), `= 1`: Info, `> 1`: Debug
- `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_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
- `saved_feature_importance_type` , default = 0, type = int
 - the feature importance type in the saved model file
 - 0: count-based feature importance (numbers of splits are counted); 1: gain-based feature importance (values of gain are counted)
 - **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

6.4 IO Parameters

6.4.1 Dataset Parameters

- `linear_tree` , default = `false`, type = `bool`, aliases: `linear_trees`
 - fit piecewise linear gradient boosting tree
 - * tree splits are chosen in the usual way, but the model at each leaf is linear instead of constant
 - * the linear model at each leaf includes all the numerical features in that leaf's branch
 - * categorical features are used for splits as normal but are not used in the linear models
 - * missing values should not be encoded as `0`. Use `np.nan` for Python, `NA` for the CLI, and `NA`, `NA_real_`, or `NA_integer_` for R
 - * it is recommended to rescale data before training so that features have similar mean and standard deviation
 - * **Note:** only works with CPU and `serial` tree learner
 - * **Note:** `regression_l1` objective is not supported with linear tree boosting
 - * **Note:** setting `linear_tree=true` significantly increases the memory use of LightGBM
 - * **Note:** if you specify `monotone_constraints`, constraints will be enforced when choosing the split points, but not when fitting the linear models on leaves
- `max_bin` , default = `255`, type = `int`, aliases: `max_bins`, 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 = `2000000`, type = `int`, aliases: `subsample_for_bin`, constraints: `bin_construct_sample_cnt > 0`
 - number of data that sampled to construct feature discrete bins
 - setting this to larger value will give better training result, but may increase data loading time
 - set this to larger value if data is very sparse
 - **Note:** don't set this to small values, otherwise, you may encounter unexpected errors and poor accuracy
- `data_random_seed` , default = `1`, type = `int`, aliases: `data_seed`
 - random seed for sampling data to construct histogram bins
- `is_enable_sparse` , default = `true`, type = `bool`, aliases: `is_sparse`, `enable_sparse`, `sparse`

- used to enable/disable sparse optimization
- `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
- `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
- `feature_pre_filter` , default = `true`, type = `bool`
 - set this to `true` (the default) to tell LightGBM to ignore the features that are unsplittable based on `min_data_in_leaf`
 - as dataset object is initialized only once and cannot be changed after that, you may need to set this to `false` when searching parameters with `min_data_in_leaf`, otherwise features are filtered by `min_data_in_leaf` firstly if you don't reconstruct dataset object
 - **Note:** setting this to `false` may slow down the training
- `pre_partition` , default = `false`, type = `bool`, aliases: `is_pre_partition`
 - used for distributed learning (excluding the `feature_parallel` mode)
 - `true` if training data are pre-partitioned, and different machines use different partitions
- `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 text file
- `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 text 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`
 - if omitted, the first column in the training data is used as the label
 - **Note:** works only in case of loading data directly from text 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 text 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 text file
 - **Note:** data should be grouped by `query_id`, for more information, see [Query Data](#)
 - **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 text 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`, `categorical_features`
 - 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 (not applicable for data represented as pandas DataFrame in Python-package)
 - **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
- `forcedbins_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
- `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:** `init_score` is not saved in binary file
 - **Note:** can be used only in CLI version; for language-specific packages you can use the correspondent function
- `precise_float_parser` , default = `false`, type = `bool`
 - use precise floating point number parsing for text parser (e.g. CSV, TSV, LibSVM input)
 - **Note:** setting this to `true` may lead to much slower text parsing
- `parser_config_file` , default = `""`, type = `string`
 - path to a `.json` file that specifies customized parser initialized configuration
 - see [lightgbm-transform](#) for usage examples
 - **Note:** `lightgbm-transform` is not maintained by LightGBM's maintainers. Bug reports or feature requests should go to [issues page](#)

6.4.2 Predict Parameters

- `start_iteration_predict` , default = `0`, type = `int`
 - used only in prediction task
 - used to specify from which iteration to start the prediction
 - `<= 0` means from the first iteration
- `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
- `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
- **Note:** this feature is not implemented for linear trees
- `predict_disable_shape_check`, default = false, type = bool
 - used only in prediction task
 - control whether or not LightGBM raises an error when you try to predict on data with a different number of features than the training data
 - if false (the default), a fatal error will be raised if the number of features in the dataset you predict on differs from the number seen during training
 - if true, LightGBM will attempt to predict on whatever data you provide. This is dangerous because you might get incorrect predictions, but you could use it in situations where it is difficult or expensive to generate some features and you are very confident that they were never chosen for splits in the model
 - **Note:** be very careful setting this parameter to true
- `pred_early_stop`, default = false, type = bool
 - used only in prediction task
 - used only in classification and ranking applications
 - used only for predicting normal or raw scores
 - if true, will use early-stopping to speed up the prediction. May affect the accuracy
 - **Note:** cannot be used with rf boosting type or custom objective function
- `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
- `output_result`, default = `LightGBM_predict_result.txt`, type = string, aliases: `predict_result`, `prediction_result`, `predict_name`, `prediction_name`, `pred_name`, `name_pred`
 - used only in prediction task
 - filename of prediction result
 - **Note:** can be used only in CLI version

6.4.3 Convert Parameters

- `convert_model_language` , default = "", type = string
 - used only in `convert_model` task
 - only `cpp` is supported yet; for conversion model to other languages consider using `m2cgen` utility
 - 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

- `objective_seed` , default = 5, type = int
 - used only in `rank_xendcg` objective
 - random seed for objectives, if random process is needed
- `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 $\sqrt{\text{label}}$ 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
- `lambdarank_truncation_level` , default = 30, type = int, constraints: `lambdarank_truncation_level > 0`
 - used only in lambdarank application
 - controls the number of top-results to focus on during training, refer to “truncation level” in the Sec. 3 of [LambdaMART paper](#)
 - this parameter is closely related to the desirable cutoff **k** in the metric **NDCG@k** that we aim at optimizing the ranker for. The optimal setting for this parameter is likely to be slightly higher than **k** (e.g., **k** + 3) to include more pairs of documents to train on, but perhaps not too high to avoid deviating too much from the desired target metric **NDCG@k**
- `lambdarank_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 lambdarank 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`, `rank_xendcg`, `xendcg`, `xe_ndcg`, `xe_ndcg_mart`, `xendcg_mart`
 - * `map`, [MAP](#), aliases: `mean_average_precision`
 - * `auc`, [AUC](#)
 - * `average_precision`, [average precision score](#)
 - * `binary_logloss`, [log loss](#), aliases: `binary`
 - * `binary_error`, for one sample: 0 for correct classification, 1 for error classification
 - * `auc_mu`, [AUC-mu](#)
 - * `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
 - **Note:** can be used only in CLI version

- `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
- `auc_mu_weights` , default = `None`, type = `multi-double`
 - used only with `auc_mu` metric
 - list representing flattened matrix (in row-major order) giving loss weights for classification errors
 - list should have `n * n` elements, where `n` is the number of classes
 - the matrix co-ordinate `[i, j]` should correspond to the `i * n + j`-th element of the list
 - if not specified, will use equal weights for all classes

6.7 Network Parameters

- `num_machines` , default = `1`, type = `int`, aliases: `num_machine`, constraints: `num_machines > 0`
 - the number of machines for distributed learning application
 - this parameter is needed to be set in both **socket** and **mpi** versions
- `local_listen_port` , default = `12400` (random for Dask-package), 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 distributed learning application
 - each line contains one IP and one port for one machine. The format is `ip port` (space as a separator)
 - **Note:** can be used only in CLI version
- `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)
 - **Note:** can be used only in OpenCL implementation, in CUDA implementation only double precision is currently supported
- `num_gpu`, default = 1, type = int, constraints: `num_gpu > 0`
 - number of GPUs
 - **Note:** can be used only in CUDA implementation

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 placed in the same folder as the data file. In this case, LightGBM will auto load initial score file if it exists.

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 learning to rank, it needs query information for training data.

LightGBM uses an additional file to store query data, like the following:

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

For wrapper libraries like in Python and R, this information can also be provided as an array-like via the Dataset parameter `group`.

```
[27, 18, 67, ...]
```

For example, if you have a 112-document dataset with `group = [27, 18, 67]`, that means that you have 3 groups, where the first 27 records are in the first group, records 28-45 are in the second group, and records 46-112 are in the third group.

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](#)
- [FLAML](#) for automated hyperparameter tuning
- [Optuna](#) for automated hyperparameter tuning

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 $2^{(\text{max_depth})}$. 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

7.2.1 Add More Computational Resources

On systems where it is available, LightGBM uses OpenMP to parallelize many operations. The maximum number of threads used by LightGBM is controlled by the parameter `num_threads`. By default, this will defer to the default behavior of OpenMP (one thread per real CPU core or the value in environment variable `OMP_NUM_THREADS`, if it is set). For best performance, set this to the number of **real** CPU cores available.

You might be able to achieve faster training by moving to a machine with more available CPU cores.

Using distributed (multi-machine) training might also reduce training time. See the [Distributed Learning Guide](#) for details.

7.2.2 Use a GPU-enabled version of LightGBM

You might find that training is faster using a GPU-enabled build of LightGBM. See the [GPU Tutorial](#) for details.

7.2.3 Grow Shallower Trees

The total training time for LightGBM increases with the total number of tree nodes added. LightGBM comes with several parameters that can be used to control the number of nodes per tree.

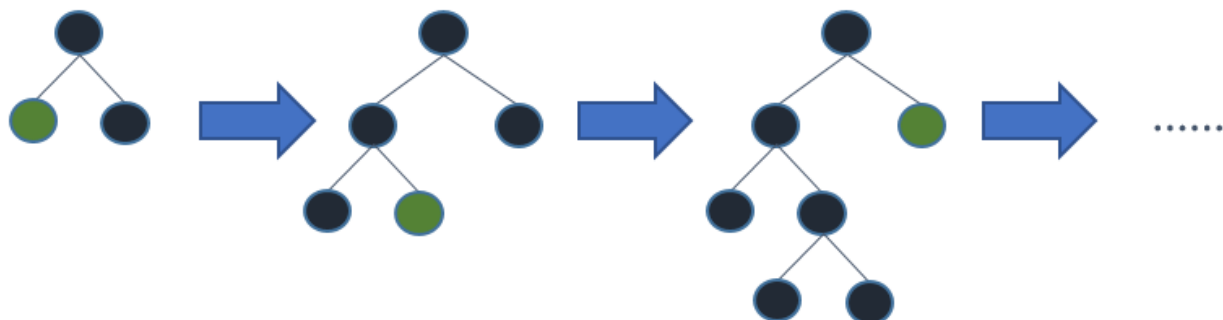
The suggestions below will speed up training, but might hurt training accuracy.

Decrease `max_depth`

This parameter is an integer that controls the maximum distance between the root node of each tree and a leaf node. Decrease `max_depth` to reduce training time.

Decrease `num_leaves`

LightGBM adds nodes to trees based on the gain from adding that node, regardless of depth. This figure from [the feature documentation](#) illustrates the process.



Leaf-wise tree growth

Because of this growth strategy, it isn't straightforward to use `max_depth` alone to limit the complexity of trees. The `num_leaves` parameter sets the maximum number of nodes per tree. Decrease `num_leaves` to reduce training time.

Increase `min_gain_to_split`

When adding a new tree node, LightGBM chooses the split point that has the largest gain. Gain is basically the reduction in training loss that results from adding a split point. By default, LightGBM sets `min_gain_to_split` to 0.0, which means “there is no improvement that is too small”. However, in practice you might find that very small improvements in the training loss don’t have a meaningful impact on the generalization error of the model. Increase `min_gain_to_split` to reduce training time.

Increase `min_data_in_leaf` and `min_sum_hessian_in_leaf`

Depending on the size of the training data and the distribution of features, it’s possible for LightGBM to add tree nodes that only describe a small number of observations. In the most extreme case, consider the addition of a tree node that only a single observation from the training data falls into. This is very unlikely to generalize well, and probably is a sign of overfitting.

This can be prevented indirectly with parameters like `max_depth` and `num_leaves`, but LightGBM also offers parameters to help you directly avoid adding these overly-specific tree nodes.

- `min_data_in_leaf`: Minimum number of observations that must fall into a tree node for it to be added.
- `min_sum_hessian_in_leaf`: Minimum sum of the Hessian (second derivative of the objective function evaluated for each observation) for observations in a leaf. For some regression objectives, this is just the minimum number of records that have to fall into each node. For classification objectives, it represents a sum over a distribution of probabilities. See [this Stack Overflow answer](#) for a good description of how to reason about values of this parameter.

7.2.4 Grow Less Trees

Decrease `num_iterations`

The `num_iterations` parameter controls the number of boosting rounds that will be performed. Since LightGBM uses decision trees as the learners, this can also be thought of as “number of trees”.

If you try changing `num_iterations`, change the `learning_rate` as well. `learning_rate` will not have any impact on training time, but it will impact the training accuracy. As a general rule, if you reduce `num_iterations`, you should increase `learning_rate`.

Choosing the right value of `num_iterations` and `learning_rate` is highly dependent on the data and objective, so these parameters are often chosen from a set of possible values through hyperparameter tuning.

Decrease `num_iterations` to reduce training time.

Use Early Stopping

If early stopping is enabled, after each boosting round the model’s training accuracy is evaluated against a validation set that contains data not available to the training process. That accuracy is then compared to the accuracy as of the previous boosting round. If the model’s accuracy fails to improve for some number of consecutive rounds, LightGBM stops the training process.

That “number of consecutive rounds” is controlled by the parameter `early_stopping_round`. For example, `early_stopping_round=1` says “the first time accuracy on the validation set does not improve, stop training”.

Set `early_stopping_round` and provide a validation set to possibly reduce training time.

7.2.5 Consider Fewer Splits

The parameters described in previous sections control how many trees are constructed and how many nodes are constructed per tree. Training time can be further reduced by reducing the amount of time needed to add a tree node to the model.

The suggestions below will speed up training, but might hurt training accuracy.

Enable Feature Pre-Filtering When Creating Dataset

By default, when a LightGBM Dataset object is constructed, some features will be filtered out based on the value of `min_data_in_leaf`.

For a simple example, consider a 1000-observation dataset with a feature called `feature_1`. `feature_1` takes on only two values: 25.0 (995 observations) and 50.0 (5 observations). If `min_data_in_leaf = 10`, there is no split for this feature which will result in a valid split at least one of the leaf nodes will only have 5 observations.

Instead of reconsidering this feature and then ignoring it every iteration, LightGBM filters this feature out at before training, when the Dataset is constructed.

If this default behavior has been overridden by setting `feature_pre_filter=False`, set `feature_pre_filter=True` to reduce training time.

Decrease `max_bin` or `max_bin_by_feature` When Creating Dataset

LightGBM training `buckets continuous features into discrete bins` to improve training speed and reduce memory requirements for training. This binning is done one time during Dataset construction. The number of splits considered when adding a node is $O(\text{\#feature} * \text{\#bin})$, so reducing the number of bins per feature can reduce the number of splits that need to be evaluated.

`max_bin` controls the maximum number of bins that features will bucketed into. It is also possible to set this maximum feature-by-feature, by passing `max_bin_by_feature`.

Reduce `max_bin` or `max_bin_by_feature` to reduce training time.

Increase `min_data_in_bin` When Creating Dataset

Some bins might contain a small number of observations, which might mean that the effort of evaluating that bin's boundaries as possible split points isn't likely to change the final model very much. You can control the granularity of the bins by setting `min_data_in_bin`.

Increase `min_data_in_bin` to reduce training time.

Decrease `feature_fraction`

By default, LightGBM considers all features in a Dataset during the training process. This behavior can be changed by setting `feature_fraction` to a value > 0 and ≤ 1.0 . Setting `feature_fraction` to 0.5, for example, tells LightGBM to randomly select 50% of features at the beginning of constructing each tree. This reduces the total number of splits that have to be evaluated to add each tree node.

Decrease `feature_fraction` to reduce training time.

Decrease `max_cat_threshold`

LightGBM uses a custom approach for finding optimal splits for categorical features. In this process, LightGBM explores splits that break a categorical feature into two groups. These are sometimes called “k-vs.-rest” splits. Higher `max_cat_threshold` values correspond to more split points and larger possible group sizes to search.

Decrease `max_cat_threshold` to reduce training time.

7.2.6 Use Less Data

Use Bagging

By default, LightGBM uses all observations in the training data for each iteration. It is possible to instead tell LightGBM to randomly sample the training data. This process of training over multiple random samples without replacement is called “bagging”.

Set `bagging_freq` to an integer greater than 0 to control how often a new sample is drawn. Set `bagging_fraction` to a value > 0.0 and < 1.0 to control the size of the sample. For example, `{"bagging_freq": 5, "bagging_fraction": 0.75}` tells LightGBM “re-sample without replacement every 5 iterations, and draw samples of 75% of the training data”.

Decrease `bagging_fraction` to reduce training time.

7.2.7 Save Constructed Datasets with `save_binary`

This only applies to the LightGBM CLI. If you pass parameter `save_binary`, the training dataset and all validations sets will be saved in a binary format understood by LightGBM. This can speed up training next time, because binning and other work done when constructing a Dataset does not have to be re-done.

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
- Try `extra_trees`
- Try increasing `path_smooth`

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.

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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_FEATURE_IMPORTANCE_GAIN (1)
Gain type of feature importance.

C_API_FEATURE_IMPORTANCE_SPLIT (0)
Split type of feature importance.

C_API_MATRIX_TYPE_CSC (1)
CSC sparse matrix type.

C_API_MATRIX_TYPE_CSR (0)
CSR sparse matrix type.

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.

INLINE_FUNCTION inline

Inline specifier.

THREAD_LOCAL thread_local

Thread local specifier.

Typedefs

typedef void ***BoosterHandle**

Handle of booster.

typedef void ***DatasetHandle**

Handle of dataset.

typedef void ***FastConfigHandle**

Handle of FastConfig.

Functions

static char ***LastErrorMsg()**

Handle of error message.

Returns Error message

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

Add new validation data to booster.

Parameters

- **handle** – Handle of booster
- **valid_data** – Validation dataset

Returns 0 when succeed, -1 when failure happens

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

Get number of predictions.

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)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **out_len** – [out] Length of prediction

Returns 0 when succeed, -1 when failure happens

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

Create a new boosting learner.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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

Load an existing booster from model file.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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

Dump model to JSON.

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
- **feature_importance_type** – Type of feature importance, can be C_API_FEATURE_IMPORTANCE_SPLIT or C_API_FEATURE_IMPORTANCE_GAIN
- **buffer_len** – String buffer length, if buffer_len < out_len, you should re-allocate buffer

- **out_len** – [out] Actual output length
- **out_str** – [out] JSON format string of model, should pre-allocate memory

Returns 0 when succeed, -1 when failure happens

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

Get model feature importance.

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:
 - C_API_FEATURE_IMPORTANCE_SPLIT: result contains numbers of times the feature is used in a model;
 - C_API_FEATURE_IMPORTANCE_GAIN: result contains total gains of splits which use the feature
- **out_results** – [out] Result array with feature importance

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterFree**(*BoosterHandle* handle)

Free space for booster.

Parameters

- **handle** – Handle of booster to be freed

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterFreePredictSparse**(void *indptr, int32_t *indices, void *data, int indptr_type, int data_type)

Method corresponding to LGBM_BoosterPredictSparseOutput to free the allocated data.

Parameters

- **indptr** – Pointer to output row headers or column headers to be deallocated
- **indices** – Pointer to sparse indices to be deallocated
- **data** – Pointer to sparse data space to be deallocated
- **indptr_type** – Type of indptr, can be C_API_DTYPE_INT32 or C_API_DTYPE_INT64
- **data_type** – Type of data pointer, can be C_API_DTYPE_FLOAT32 or C_API_DTYPE_FLOAT64

Returns 0 when succeed, -1 when failure happens

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

Get index of the current boosting iteration.

Parameters

- **handle** – Handle of booster
- **out_iteration** – [out] Index of the current boosting iteration

Returns 0 when succeed, -1 when failure happens

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:

- a. You should call LGBM_BoosterGetEvalNames first to get the names of evaluation metrics.
 - b. You should pre-allocate memory for out_results, you can get its length by LGBM_BoosterGetEvalCounts.
-

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_len** – [out] Length of output result
- **out_results** – [out] Array with evaluation results

Returns 0 when succeed, -1 when failure happens

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

Get number of evaluation metrics.

Parameters

- **handle** – Handle of booster
- **out_len** – [out] Total number of evaluation metrics

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetEvalNames**(*BoosterHandle* handle, const int len, int *out_len, const size_t buffer_len, size_t *out_buffer_len, char **out_strs)

Get names of evaluation metrics.

Parameters

- **handle** – Handle of booster
- **len** – Number of char* pointers stored at out_strs. If smaller than the max size, only this many strings are copied
- **out_len** – [out] Total number of evaluation metrics
- **buffer_len** – Size of pre-allocated strings. Content is copied up to buffer_len - 1 and null-terminated
- **out_buffer_len** – [out] String sizes required to do the full string copies
- **out_strs** – [out] Names of evaluation metrics, should pre-allocate memory

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetFeatureNames**(*BoosterHandle* handle, const int len, int *out_len, const size_t buffer_len, size_t *out_buffer_len, char **out_strs)

Get names of features.

Parameters

- **handle** – Handle of booster
- **len** – Number of `char*` pointers stored at `out_strs`. If smaller than the max size, only this many strings are copied
- **out_len** – [out] Total number of features
- **buffer_len** – Size of pre-allocated strings. Content is copied up to `buffer_len - 1` and null-terminated
- **out_buffer_len** – [out] String sizes required to do the full string copies
- **out_strs** – [out] Names of features, should pre-allocate memory

Returns 0 when succeed, -1 when failure happens

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

Get leaf value.

Parameters

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

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetLinear**(*BoosterHandle* handle, int *out)

Get int representing whether booster is fitting linear trees.

Parameters

- **handle** – Handle of booster
- **out** – [out] The address to hold linear trees indicator

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetLowerBoundValue**(*BoosterHandle* handle, double *out_results)

Get model lower bound value.

Parameters

- **handle** – Handle of booster
- **out_results** – [out] Result pointing to min value

Returns 0 when succeed, -1 when failure happens

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

Get number of classes.

Parameters

- **handle** – Handle of booster
- **out_len** – [out] Number of classes

Returns 0 when succeed, -1 when failure happens

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

Get number of features.

Parameters

- **handle** – Handle of booster
- **out_len** – [out] Total number of features

Returns 0 when succeed, -1 when failure happens

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).

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_len** – [out] Number of predictions

Returns 0 when succeed, -1 when failure happens

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`.

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_len** – [out] Length of output result
- **out_result** – [out] Pointer to array with predictions

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetUpperBoundValue**(*BoosterHandle* handle, double *out_results)

Get model upper bound value.

Parameters

- **handle** – Handle of booster
- **out_results** – [out] Result pointing to max value

Returns 0 when succeed, -1 when failure happens

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

Load an existing booster from string.

Parameters

- **model_str** – Model string
- **out_num_iterations** – [out] Number of iterations of this booster

- **out** – [out] Handle of created booster

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterMerge**(*BoosterHandle* handle, *BoosterHandle* other_handle)
Merge model from other_handle into handle.

Parameters

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

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterNumberOfTotalModel**(*BoosterHandle* handle, int *out_models)
Get number of weak sub-models.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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

Get number of trees per iteration.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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 nelelem,
int64_t num_row, int predict_type, int
start_iteration, 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).
-

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)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iteration for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – [out] Length of output result
- **out_result** – [out] Pointer to array with predictions

Returns 0 when succeed, -1 when failure happens

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 start_iteration, 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).
-

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)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – [out] Length of output result
- **out_result** – [out] Pointer to array with predictions

Returns 0 when succeed, -1 when failure happens

```
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
                                                         start_iteration, 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).
-

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)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, ≤ 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – [out] Length of output result
- **out_result** – [out] Pointer to array with predictions

Returns 0 when succeed, -1 when failure happens

```

LIGHTGBM_C_EXPORT int LGBM_BoosterPredictForCSRSingleRowFast(FastConfigHandle
                                                             fastConfig_handle, const void
                                                             *indptr, const int indptr_type,
                                                             const int32_t *indices, const void
                                                             *data, const int64_t nindptr, const
                                                             int64_t nelem, int64_t *out_len,
                                                             double *out_result)

```

Faster variant of LGBM_BoosterPredictForCSRSingleRow.

Score single rows after setup with LGBM_BoosterPredictForCSRSingleRowFastInit.

By removing the setup steps from this call extra optimizations can be made like initializing the config only once, instead of once per call.

Note: Setting up the number of threads is only done once at LGBM_BoosterPredictForCSRSingleRowFastInit instead of at each prediction. If you use a different number of threads in other calls, you need to start the setup process over, or that number of threads will be used for these calls as well.

Note: You should pre-allocate memory for out_result:

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

Parameters

- **fastConfig_handle** – FastConfig object handle returned by LGBM_BoosterPredictForCSRSingleRowFastInit
- **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

- **nindptr** – Number of rows in the matrix + 1
- **nelem** – Number of nonzero elements in the matrix
- **out_len** – [out] Length of output result
- **out_result** – [out] Pointer to array with predictions

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForCSRSingleRowFastInit**(*BoosterHandle* handle, const int predict_type, const int start_iteration, const int num_iteration, const int data_type, const int64_t num_col, const char *parameter, *FastConfigHandle* *out_fastConfig)

Initialize and return a FastConfigHandle for use with LGBM_BoosterPredictForCSRSingleRowFast.

Release the FastConfig by passing its handle to LGBM_FastConfigFree when no longer needed.

Parameters

- **handle** – Booster handle
- **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)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **data_type** – Type of data pointer, can be C_API_DTYPE_FLOAT32 or C_API_DTYPE_FLOAT64
- **num_col** – Number of columns
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_fastConfig** – [out] FastConfig object with which you can call LGBM_BoosterPredictForCSRSingleRowFast

Returns 0 when it succeeds, -1 when failure happens

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

Make prediction for file.

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)
- **start_iteration** – Start index of the iteration to predict
- **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

Returns 0 when succeed, -1 when failure happens

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 start_iteration, 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 $\text{num_class} * \text{num_data}$;
 - for leaf index, its length is equal to $\text{num_class} * \text{num_data} * \text{num_iteration}$;
 - for feature contributions, its length is equal to $\text{num_class} * \text{num_data} * (\text{num_feature} + 1)$.
-

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)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iteration for prediction, ≤ 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction

- **out_len** – [out] Length of output result
- **out_result** – [out] Pointer to array with predictions

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForMats**(*BoosterHandle* handle, const void **data, int data_type, int32_t nrow, int32_t ncol, int predict_type, int start_iteration, int num_iteration, const char *parameter, 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)`.
-

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)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iteration for prediction, `<= 0` means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – [out] Length of output result
- **out_result** – [out] Pointer to array with predictions

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForMatSingleRow**(*BoosterHandle* handle, const void *data, int data_type, int ncol, int is_row_major, int predict_type, int start_iteration, 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)`.
-

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)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iteration for prediction, `<= 0` means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – [out] Length of output result
- **out_result** – [out] Pointer to array with predictions

Returns 0 when succeed, -1 when failure happens

```

LIGHTGBM_C_EXPORT int LGBM_BoosterPredictForMatSingleRowFast(FastConfigHandle
                                                             fastConfig_handle, const void
                                                             *data, int64_t *out_len, double
                                                             *out_result)

```

Faster variant of `LGBM_BoosterPredictForMatSingleRow`.

Score a single row after setup with `LGBM_BoosterPredictForMatSingleRowFastInit`.

By removing the setup steps from this call extra optimizations can be made like initializing the config only once, instead of once per call.

Note: Setting up the number of threads is only done once at `LGBM_BoosterPredictForMatSingleRowFastInit` instead of at each prediction. If you use a different number of threads in other calls, you need to start the setup process over, or that number of threads will be used for these calls as well.

Parameters

- **fastConfig_handle** – FastConfig object handle returned by LGBM_BoosterPredictForMatSingleRowFastInit
- **data** – Single-row array data (no other way than row-major form).
- **out_len** – [out] Length of output result
- **out_result** – [out] Pointer to array with predictions

Returns 0 when it succeeds, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForMatSingleRowFastInit**(*BoosterHandle* handle, const int predict_type, const int start_iteration, const int num_iteration, const int data_type, const int32_t ncol, const char *parameter, *FastConfigHandle* *out_fastConfig)

Initialize and return a FastConfigHandle for use with LGBM_BoosterPredictForMatSingleRowFast.

Release the FastConfig by passing its handle to LGBM_FastConfigFree when no longer needed.

Parameters

- **handle** – Booster handle
- **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)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **data_type** – Type of data pointer, can be C_API_DTYPE_FLOAT32 or C_API_DTYPE_FLOAT64
- **ncol** – Number of columns
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_fastConfig** – [out] FastConfig object with which you can call LGBM_BoosterPredictForMatSingleRowFast

Returns 0 when it succeeds, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictSparseOutput**(*BoosterHandle* handle, const void *indptr, int indptr_type, const int32_t *indices, const void *data, int data_type, int64_t nindptr, int64_t nelelem, int64_t num_col_or_row, int predict_type, int start_iteration, int num_iteration, const char *parameter, int matrix_type, int64_t *out_len, void **out_indptr, int32_t **out_indices, void **out_data)

Make sparse prediction for a new dataset in CSR or CSC format. Currently only used for feature contributions.

Note: The outputs are pre-allocated, as they can vary for each invocation, but the shape should be the same:

- for feature contributions, the shape of sparse matrix will be `num_class * num_data * (num_feature + 1)`. The output `indptr_type` for the sparse matrix will be the same as the given input `indptr_type`. Call `LGBM_BoosterFreePredictSparse` to deallocate resources.
-

Parameters

- **handle** – Handle of booster
- **indptr** – Pointer to row headers for CSR or column headers for CSC
- **indptr_type** – Type of `indptr`, can be `C_API_DTYPE_INT32` or `C_API_DTYPE_INT64`
- **indices** – Pointer to column indices for CSR or row indices for CSC
- **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_or_row** – Number of columns for CSR or number of rows for CSC
- **predict_type** – What should be predicted, only feature contributions supported currently
 - `C_API_PREDICT_CONTRIB`: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, `<= 0` means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **matrix_type** – Type of matrix input and output, can be `C_API_MATRIX_TYPE_CSR` or `C_API_MATRIX_TYPE_CSC`
- **out_len** – [out] Length of output indices and data
- **out_indptr** – [out] Pointer to output row headers for CSR or column headers for CSC
- **out_indices** – [out] Pointer to sparse column indices for CSR or row indices for CSC
- **out_data** – [out] Pointer to sparse data space

Returns 0 when succeed, -1 when failure happens

`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).

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`

Returns 0 when succeed, -1 when failure happens

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

Parameters

- **handle** – Handle of booster
- **parameters** – Parameters in format ‘key1=value1 key2=value2’

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterResetTrainingData**(*BoosterHandle* handle, const *DatasetHandle* train_data)

Reset training data for booster.

Parameters

- **handle** – Handle of booster
- **train_data** – Training dataset

Returns 0 when succeed, -1 when failure happens

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

Parameters

- **handle** – Handle of booster

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterSaveModel**(*BoosterHandle* handle, int start_iteration, int num_iteration, int feature_importance_type, const char *filename)

Save model into file.

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
- **feature_importance_type** – Type of feature importance, can be C_API_FEATURE_IMPORTANCE_SPLIT or C_API_FEATURE_IMPORTANCE_GAIN
- **filename** – The name of the file

Returns 0 when succeed, -1 when failure happens

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

Save model to string.

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

- **feature_importance_type** – Type of feature importance, can be C_API_FEATURE_IMPORTANCE_SPLIT or C_API_FEATURE_IMPORTANCE_GAIN
- **buffer_len** – String buffer length, if `buffer_len < out_len`, you should re-allocate buffer
- **out_len** – [out] Actual output length
- **out_str** – [out] String of model, should pre-allocate memory

Returns 0 when succeed, -1 when failure happens

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

Set leaf value.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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

Shuffle models.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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

Update the model for one iteration.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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).

Parameters

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

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetAddFeaturesFrom**(*DatasetHandle* target, *DatasetHandle* source)
Add features from source to target.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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.

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

Returns 0 when succeed, -1 when failure happens

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.

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

Returns 0 when succeed, -1 when failure happens

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.

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

Returns 0 when succeed, -1 when failure happens

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).

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

Returns 0 when succeed, -1 when failure happens

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.

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

Returns 0 when succeed, -1 when failure happens

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.

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

Returns 0 when succeed, -1 when failure happens

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.

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

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetDumpText**(*DatasetHandle* handle, const char *filename)
Save dataset to text file, intended for debugging use only.

Parameters

- **handle** – Handle of dataset
- **filename** – The name of the file

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetFree**(*DatasetHandle* handle)
Free space for dataset.

Parameters

- **handle** – Handle of dataset to be freed

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetFeatureNames**(*DatasetHandle* handle, const int len, int
*num_feature_names, const size_t buffer_len,
size_t *out_buffer_len, char **feature_names)

Get feature names of dataset.

Parameters

- **handle** – Handle of dataset
- **len** – Number of char* pointers stored at out_strs. If smaller than the max size, only this many strings are copied
- **num_feature_names** – [out] Number of feature names
- **buffer_len** – Size of pre-allocated strings. Content is copied up to buffer_len - 1 and null-terminated
- **out_buffer_len** – [out] String sizes required to do the full string copies
- **feature_names** – [out] Feature names, should pre-allocate memory

Returns 0 when succeed, -1 when failure happens

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.

Parameters

- **handle** – Handle of dataset

- **field_name** – Field name
- **out_len** – [out] Used to set result length
- **out_ptr** – [out] Pointer to the result
- **out_type** – [out] Type of result pointer, can be C_API_DTYPE_INT32, C_API_DTYPE_FLOAT32 or C_API_DTYPE_FLOAT64

Returns 0 when succeed, -1 when failure happens

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

Get number of data points.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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

Get number of features.

Parameters

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

Returns 0 when succeed, -1 when failure happens

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.

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

Returns 0 when succeed, -1 when failure happens

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.

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

Returns 0 when succeed, -1 when failure happens

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 nelelem, int64_t num_col, int64_t start_row)

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

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
- **nelelem** – Number of nonzero elements in the matrix
- **num_col** – Number of columns
- **start_row** – Row start index

Returns 0 when succeed, -1 when failure happens

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

Parameters

- **handle** – Handle of dataset
- **filename** – The name of the file

Returns 0 when succeed, -1 when failure happens

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

Save feature names to dataset.

Parameters

- **handle** – Handle of dataset
- **feature_names** – Feature names
- **num_feature_names** – Number of feature names

Returns 0 when succeed, -1 when failure happens

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.
-

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

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetUpdateParamChecking**(const char *old_parameters, const char *new_parameters)

Raise errors for attempts to update dataset parameters.

Parameters

- **old_parameters** – Current dataset parameters
- **new_parameters** – New dataset parameters

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DumpParamAliases**(int64_t buffer_len, int64_t *out_len, char *out_str)
Dump all parameter names with their aliases to JSON.

Parameters

- **buffer_len** – String buffer length, if *buffer_len* < *out_len*, you should re-allocate buffer
- **out_len** – [out] Actual output length
- **out_str** – [out] JSON format string of parameters, should pre-allocate memory

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_FastConfigFree**(*FastConfigHandle* fastConfig)
Release FastConfig object.

Parameters

- **fastConfig** – Handle to the FastConfig object acquired with a **FastInit()* method.

Returns 0 when it succeeds, -1 when failure happens

LIGHTGBM_C_EXPORT const char ***LGBM_GetLastError**()
Get string message of the last error.

Returns Error information

LIGHTGBM_C_EXPORT int **LGBM_GetSampleCount**(int32_t num_total_row, const char *parameters, int *out)
Get number of samples based on parameters and total number of rows of data.

Parameters

- **num_total_row** – Number of total rows

- **parameters** – Additional parameters, namely, `bin_construct_sample_cnt` is used to calculate returned value
- **out** – **[out]** Number of samples. This value is used to pre-allocate memory to hold sample indices when calling `LGBM_SampleIndices`

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_NetworkFree**()

Finalize the network.

Returns 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.

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

Returns 0 when succeed, -1 when failure happens

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.

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

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_RegisterLogCallback**(void (*callback)(const char*))

Register a callback function for log redirecting.

Parameters

- **callback** – The callback function to register

Returns 0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_SampleIndices**(int32_t num_total_row, const char *parameters, void *out, int32_t *out_len)

Create sample indices for total number of rows.

Note: You should pre-allocate memory for out, you can get its length by `LGBM_GetSampleCount`.

Parameters

- **num_total_row** – Number of total rows

- **parameters** – Additional parameters, namely, `bin_construct_sample_cnt` and `data_random_seed` are used to produce the output
- **out** – [out] Created indices, type is `int32_t`
- **out_len** – [out] Number of indices

Returns 0 when succeed, -1 when failure happens

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

Note: This will call unsafe `sprintf` when compiled using C standards before C99.

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.
<code>CVBooster()</code>	CVBooster in LightGBM.
<code>Sequence()</code>	Generic data access interface.

9.1.1 `lightgbm.Dataset`

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

Initialize Dataset.

Parameters

- **data** (*str*, *pathlib.Path*, *numpy array*, *pandas DataFrame*, *H2O DataTable's Frame*, *scipy.sparse*, *Sequence*, *list of Sequence* or *list of numpy array*) – Data source of Dataset. If *str* or *pathlib.Path*, it represents the path to a text file (CSV, TSV, or LibSVM) or a LightGBM Dataset binary 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 data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

- **init_score** (*list, list of lists (for multi-class task), numpy array, pandas Series, pandas DataFrame (for multi-class task), or None, optional (default=None)*) – Init score for Dataset.
- **feature_name** (*list of str, or 'auto', optional (default="auto")*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default="auto")*) – Categorical features. If list of int, interpreted as indices. If list of str, 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_name()</code>	Get the names of columns (features) in 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_params()</code>	Get the used parameters in 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.
<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, params=None*)

Create validation data align with current Dataset.

Parameters

- **data** (*str, pathlib.Path, numpy array, pandas DataFrame, H2O DataTable's Frame, scipy.sparse, Sequence, list of Sequence or list of numpy array*) – Data source of Dataset. If str or pathlib.Path, it represents the path to a text file (CSV, TSV, or LibSVM) or a LightGBM Dataset binary 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 data. Only used in the learning-to-rank task. $\text{sum}(\text{group}) = n_samples$. For example, if you have a 100-document dataset with **group** = [10, 20, 40, 10, 10, 10], that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
- **init_score** (*list, list of lists (for multi-class task), numpy array, pandas Series, pandas DataFrame (for multi-class task), or None, optional (default=None)*) – Init score for Dataset.
- **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 *str, pathlib.Path, numpy array, pandas DataFrame, H2O DataTable's Frame, scipy.sparse, Sequence, list of Sequence or list of numpy array or None*

get_feature_name()

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

Returns **feature_names** – The names of columns (features) in the Dataset.

Return type *list of str*

get_field(*field_name*)

Get property from the Dataset.

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

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

Return type numpy array or None

get_group()

Get the group of the Dataset.

Returns **group** – Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

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_params()

Get the used parameters in the Dataset.

Returns **params** – The used parameters in this Dataset object.

Return type dict 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.

Note: Please note that *init_score* is not saved in binary file. If you need it, please set it again after loading Dataset.

Parameters **filename** (*str or pathlib.Path*) – 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 str*) – 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 str*) – 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** (*str*) – The field name of the information.
- **data** (*list, list of lists (for multi-class task), numpy array, pandas Series, pandas DataFrame (for multi-class task), or None*) – The 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/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

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, list of lists (for multi-class task), numpy array, pandas Series, pandas DataFrame (for multi-class task), 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*)

Bases: object

Booster in LightGBM.

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

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** (*str, pathlib.Path or None, optional (default=None)*) – Path to the model file.
- **model_str** (*str or None, optional (default=None)*) – Model will be loaded from this string.

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>lower_bound()</code>	Get lower bound value of a model.
<code>model_from_string(model_str)</code>	Load Booster from a string.
<code>model_to_string([num_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[, start_iteration, ...])</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.

continues on next page

Table 3 – continued from previous page

<code>trees_to_dataframe()</code>	Parse the fitted model and return in an easy-to-read pandas DataFrame.
<code>update([train_set, fobj])</code>	Update Booster for one iteration.
<code>upper_bound()</code>	Get upper bound value of a model.

add_valid(*data*, *name*)

Add validation data.

Parameters

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

Returns *self* – Booster with set validation data.

Return type *Booster*

attr(*key*)

Get attribute string from the Booster.

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

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

Return type *str* 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*, *importance_type='split'*, *object_hook=None*)

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.
- **importance_type** (*str*, *optional* (*default="split"*)) – What type of feature importance should be dumped. 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.
- **object_hook** (*callable* or *None*, *optional* (*default=None*)) – If not None, *object_hook* is a function called while parsing the json string returned by the C API. It may be used to alter the json, to store specific values while building the json structure. It avoids walking through the structure again. It saves a significant amount of time if the number of trees is huge. Signature is `def object_hook(node: dict) -> dict`. None is equivalent to `lambda node: node`. See documentation of `json.loads()` for further details.

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** (*str*) – 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 [numpy 1-D array] The predicted values. If *fobj* is specified, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

eval_data [*Dataset*] The evaluation dataset.

eval_name [*str*] The name of evaluation function (without whitespace).

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 [numpy 1-D array] The predicted values. If *fobj* is specified, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

train_data [*Dataset*] The training dataset.

eval_name [*str*] The name of evaluation function (without whitespace).

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 [numpy 1-D array] The predicted values. If `fobj` is specified, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

valid_data [Dataset] The validation dataset.

eval_name [str] The name of evaluation function (without whitespace).

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**(*str, 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 of str

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

Warning: Categorical features are not supported.

- **bins** (*int*, *str* 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 *str*, 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.

lower_bound()

Get lower bound value of a model.

Returns **lower_bound** – Lower bound value of the model.

Return type double

model_from_string(*model_str*)

Load Booster from a string.

Parameters **model_str** (*str*) – Model will be loaded from this string.

Returns **self** – Loaded Booster object.

Return type *Booster*

model_to_string(*num_iteration=None*, *start_iteration=0*, *importance_type='split'*)

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.

- **importance_type**(*str, optional (default="split")*) – What type of feature importance should be saved. 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.

Returns **str_repr** – String representation of Booster.

Return type **str**

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, start_iteration=0, 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** (*str, pathlib.Path, numpy array, pandas DataFrame, H2O DataTable's Frame or scipy.sparse*) – Data source for prediction. If *str* or *pathlib.Path*, it represents the path to a text file (CSV, TSV, or LibSVM).
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If ≤ 0 , starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If *None*, if the best iteration exists and *start_iteration* ≤ 0 , the best iteration is used; otherwise, all iterations from *start_iteration* are used (no limits). If ≤ 0 , all iterations from *start_iteration* 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 *str*.

- **is_reshape** (*bool, optional (default=True)*) – If True, result is reshaped to [nrow, ncol].
- ****kwargs** – Other parameters for the prediction.

Returns result – Prediction result. Can be sparse or a list of sparse objects (each element represents predictions for one class) for feature contributions (when `pred_contrib=True`).

Return type numpy array, scipy.sparse or list of scipy.sparse

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

Parameters

- **data** (*str, pathlib.Path, numpy array, pandas DataFrame, H2O DataTable's Frame or scipy.sparse*) – Data source for refit. If str or pathlib.Path, it represents the path to a text file (CSV, TSV, or LibSVM).
- **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, importance_type='split'*)
Save Booster to file.

Parameters

- **filename** (*str or pathlib.Path*) – 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.
- **importance_type** (*str, optional (default="split")*) – What type of feature importance should be saved. 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.

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 str*) – 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 distributed 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** (*str*) – 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*

trees_to_dataframe()

Parse the fitted model and return in an easy-to-read pandas DataFrame.

The returned DataFrame has the following columns.

- **tree_index** : int64, which tree a node belongs to. 0-based, so a value of 6, for example, means “this node is in the 7th tree”.
- **node_depth** : int64, how far a node is from the root of the tree. The root node has a value of 1, its direct children are 2, etc.

- **node_index** : str, unique identifier for a node.
- **left_child** : str, **node_index** of the child node to the left of a split. **None** for leaf nodes.
- **right_child** : str, **node_index** of the child node to the right of a split. **None** for leaf nodes.
- **parent_index** : str, **node_index** of this node's parent. **None** for the root node.
- **split_feature** : str, name of the feature used for splitting. **None** for leaf nodes.
- **split_gain** : float64, gain from adding this split to the tree. NaN for leaf nodes.
- **threshold** : float64, value of the feature used to decide which side of the split a record will go down. NaN for leaf nodes.
- **decision_type** : str, logical operator describing how to compare a value to **threshold**. For example, **split_feature** = "Column_10", **threshold** = 15, **decision_type** = "<=" means that records where **Column_10** <= 15 follow the left side of the split, otherwise follows the right side of the split. **None** for leaf nodes.
- **missing_direction** : str, split direction that missing values should go to. **None** for leaf nodes.
- **missing_type** : str, describes what types of values are treated as missing.
- **value** : float64, predicted value for this leaf node, multiplied by the learning rate.
- **weight** : float64 or int64, sum of hessian (second-order derivative of objective), summed over observations that fall in this node.
- **count** : int64, number of records in the training data that fall into this node.

Returns result – Returns a pandas DataFrame of the parsed model.

Return type pandas DataFrame

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 [numpy 1-D array] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

train_data [Dataset] The training dataset.

grad [list, numpy 1-D array or pandas Series] The value of the first order derivative (gradient) of the loss with respect to the elements of **preds** for each sample point.

hess [list, numpy 1-D array or pandas Series] The value of the second order derivative (Hessian) of the loss with respect to the elements of **preds** 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

upper_bound()

Get upper bound value of a model.

Returns **upper_bound** – Upper bound value of the model.

Return type double

9.1.3 lightgbm.CVBooster

class lightgbm.CVBooster

Bases: object

CVBooster in LightGBM.

Auxiliary data structure to hold and redirect all boosters of cv function. This class has the same methods as Booster class. All method calls are actually performed for underlying Boosters and then all returned results are returned in a list.

boosters

The list of underlying fitted models.

Type list of Booster

best_iteration

The best iteration of fitted model.

Type int

__init__()

Initialize the CVBooster.

Generally, no need to instantiate manually.

Methods

__init__()

Initialize the CVBooster.

9.1.4 lightgbm.Sequence

class lightgbm.Sequence

Bases: abc.ABC

Generic data access interface.

Object should support the following operations:

```
# Get total row number.
>>> len(seq)
# Random access by row index. Used for data sampling.
>>> seq[10]
# Range data access. Used to read data in batch when constructing Dataset.
>>> seq[0:100]
# Optionally specify batch_size to control range data read size.
>>> seq.batch_size
```

- With random access, **data sampling does not need to go through all data**.
- With range data access, there's **no need to read all data into memory thus reduce memory usage**.

New in version 3.3.0.

batch_size

Default size of a batch.

Type int

`__init__()`

Methods

`__init__()`

Attributes

`batch_size`

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', 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 Dataset, or None, optional (default=None)*) – List of data to be evaluated on during training.
- **valid_names** (*list of str, 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 [numpy 1-D array] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

train_data [Dataset] The training dataset.

grad [list, numpy 1-D array or pandas Series] The value of the first order derivative (gradient) of the loss with respect to the elements of preds for each sample point.

hess [list, numpy 1-D array or pandas Series] The value of the second order derivative (Hessian) of the loss with respect to the elements of preds 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, list of callable, or None, optional (default=None)*) – Customized evaluation function. Each evaluation function should accept two parameters: preds, train_data, and return (eval_name, eval_result, is_higher_better) or list of such tuples.

preds [numpy 1-D array] The predicted values. If fobj is specified, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

train_data [Dataset] The training dataset.

eval_name [str] 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** (*(str, pathlib.Path, Booster or None, optional (default=None))*) – Filename of LightGBM model or Booster instance used for continue training.
- **feature_name** (*(list of str, or 'auto', optional (default="auto"))*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*(list of str or int, or 'auto', optional (default="auto"))*) – Categorical features. If list of int, interpreted as indices. If list of str, 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.
- **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. This means you won't be able to use `eval`, `eval_train` or `eval_valid` methods of the returned Booster. When your model is very

large and cause the memory error, you can try to set this param to True to avoid the model conversion performed during the internal call of `model_to_string`. You can still use `_InnerPredictor` as `init_model` for future continue training.

- **callbacks** (*list of callable, 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', fpreproc=None, seed=0, callbacks=None, eval_train_metric=False, return_cvbooster=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** (*str, list of str, 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 [numpy 1-D array] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

train_data [Dataset] The training dataset.

grad [list, numpy 1-D array or pandas Series] The value of the first order derivative (gradient) of the loss with respect to the elements of `preds` for each sample point.

hess [list, numpy 1-D array or pandas Series] The value of the second order derivative (Hessian) of the loss with respect to the elements of preds 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, list of callable, or None, optional (default=None)*) – Customized evaluation function. Each evaluation function should accept two parameters: preds, train_data, and return (eval_name, eval_result, is_higher_better) or list of such tuples.

preds [numpy 1-D array] The predicted values. If fobj is specified, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

train_data [Dataset] The training dataset.

eval_name [str] The name of evaluation function (without whitespace).

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** (*str, pathlib.Path, Booster or None, optional (default=None)*) – Filename of LightGBM model or Booster instance used for continue training.
- **feature_name** (*list of str, or 'auto', optional (default="auto")*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default="auto")*) – Categorical features. If list of int, interpreted as indices. If list of str, 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.
- **fpreproc** (*callable or None, optional (default=None)*) – Preprocessing function that takes (dtrain, dtest, params) and returns transformed versions of those.
- **seed** (*int, optional (default=0)*) – Seed used to generate the folds (passed to numpy.random.seed).
- **callbacks** (*list of callable, 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.
- **return_cvbooster** (*bool, optional (default=False)*) – Whether to return Booster models trained on each fold through CVBooster.

Returns `eval_hist` – Evaluation history. The dictionary has the following format: {‘metric1-mean’: [values], ‘metric1-stdv’: [values], ‘metric2-mean’: [values], ‘metric2-stdv’: [values], ... }. If `return_cvbooster=True`, also returns trained boosters via `cvbooster` key.

Return type dict

9.3 Scikit-learn API

<code>LGBMModel(*args, **kwargs)</code>	Implementation of the scikit-learn API for LightGBM.
<code>LGBMClassifier(*args, **kwargs)</code>	LightGBM classifier.
<code>LGBMRegressor(*args, **kwargs)</code>	LightGBM regressor.
<code>LGBMRanker(*args, **kwargs)</code>	LightGBM ranker.

9.3.1 `lightgbm.LGBMModel`

class `lightgbm.LGBMModel(*args, **kwargs)`

Bases: `sklearn.base.BaseEstimator`

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, *importance_type*='split', **kwargs)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str*, 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** (*str*, 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*, *RandomState* object or None, optional (default=None)) – Random number seed. If `int`, this number is used to seed the C++ code. If *RandomState* object (numpy), a random integer is picked based on its state to seed the C++ code. If None, default seeds in C++ code are used.
- **n_jobs** (*int*, optional (default=-1)) – Number of parallel threads to use for training (can be changed at prediction time).
- **importance_type** (*str*, 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.

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. $\text{sum}(\text{group}) = \text{n_samples}$. For example, if you have a 100-document dataset with **group** = [10, 20, 40, 10, 10, 10], that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

grad [list, numpy 1-D array or pandas Series of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of y_pred for each sample point.

hess [list, numpy 1-D array or pandas Series of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of y_pred 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, start_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>	The best iteration of fitted model if <code>early_stopping()</code> callback has been specified.
<code>best_score_</code>	The best score of fitted model.
<code>booster_</code>	The underlying Booster of this model.
<code>evals_result_</code>	The evaluation results if validation sets have been specified.
<code>feature_importances_</code>	The feature importances (the higher, the more important).
<code>feature_name_</code>	The names of features.
<code>n_estimators_</code>	True number of boosting iterations performed.
<code>n_features_</code>	The number of features of fitted model.
<code>n_features_in_</code>	The number of features of fitted model.
<code>n_iter_</code>	True number of boosting iterations performed.
<code>objective_</code>	The concrete objective used while fitting this model.

property `best_iteration_`

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type `int`

property `best_score_`

The best score of fitted model.

Type `dict`

property `booster_`

The underlying Booster of this model.

Type *Booster*

property `evals_result_`

The evaluation results if validation sets have been specified.

Type `dict`

property `feature_importances_`

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

Note: `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type `array` of shape = `[n_features]`

property `feature_name_`

The names of features.

Type `array` of shape = `[n_features]`

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, *feature_name*='auto', *categorical_feature*='auto', *callbacks*=None, *init_model*=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 shape = `[n_samples * n_classes]` (for multi-class task) or shape = `[n_samples, n_classes]` (for multi-class task) or None, optional (default=None)) – Init score of training data.
- **group** (array-like or None, optional (default=None)) – Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

- **eval_set** (*list or None, optional (default=None)*) – A list of (X, y) tuple pairs to use as validation sets.
- **eval_names** (*list of str, or None, optional (default=None)*) – Names of eval_set.
- **eval_sample_weight** (*list of array, 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 array, or None, optional (default=None)*) – Init score of eval data.
- **eval_group** (*list of array, or None, optional (default=None)*) – Group data of eval data.
- **eval_metric** (*str, callable, list or None, optional (default=None)*) – If str, 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. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. 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.
- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, 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 callable, or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.
- **init_model** (*str, pathlib.Path, Booster, LGBMModel or None, optional (default=None)*) – Filename of LightGBM model, Booster instance or LGBMModel instance used for continue training.

Returns **self** – Returns self.

Return type *LGBMModel*

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. In case of custom objective, predicted values

are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight [numpy 1-D array of shape = [n_samples]] The weight of samples.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. $\text{sum}(\text{group}) = \text{n_samples}$. For example, if you have a 100-document dataset with **group** = [10, 20, 40, 10, 10, 10], that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

eval_name [str] The name of evaluation function (without whitespace).

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

property **n_estimators_**

True number of boosting iterations performed.

This might be less than parameter **n_estimators** if early stopping was enabled or if boosting stopped early due to limits on complexity like **min_gain_to_split**.

Type int

property **n_features_**

The number of features of fitted model.

Type int

property **n_features_in_**

The number of features of fitted model.

Type int

property **n_iter_**

True number of boosting iterations performed.

This might be less than parameter **n_estimators** if early stopping was enabled or if boosting stopped early due to limits on complexity like **min_gain_to_split**.

Type int

property **objective_**

The concrete objective used while fitting this model.

Type str or callable

predict(*X, raw_score=False, start_iteration=0, 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.
- **start_iteration** (int, optional (default=0)) – Start index of the iteration to predict. If ≤ 0 , starts from the first iteration.
- **num_iteration** (int or None, optional (default=None)) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration ≤ 0 , the best iteration is used; otherwise, all iterations from start_iteration are used (no limits). If ≤ 0 , all iterations from start_iteration 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 = $[n_samples, (n_features + 1) * n_classes]$ or list with $n_classes$ length of such objects) – 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(*args, **kwargs)

Bases: sklearn.base.ClassifierMixin, [lightgbm.sklearn.LGBMModel](#)

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, subsample=1.0, subsample_freq=0,
          colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=-1,
          importance_type='split', **kwargs)
```

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str*, *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** (*str*, *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 $n_{\text{samples}} / (n_{\text{classes}} * \text{np.bincount}(y))$. 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, RandomState object or None, optional (default=None)*) – Random number seed. If *int*, this number is used to seed the C++ code. If *RandomState* object (numpy), a random integer is picked based on its state to seed the C++ code. If *None*, default seeds in C++ code are used.
- **n_jobs**(*int, optional (default=-1)*) – Number of parallel threads to use for training (can be changed at prediction time).
- **importance_type**(*str, 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.

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

grad [list, numpy 1-D array or pandas Series of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of `y_pred` for each sample point.

hess [list, numpy 1-D array or pandas Series of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of `y_pred` 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, start_iteration, ...])</code>	Return the predicted value for each sample.
<code>predict_proba(X[, raw_score, ...])</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>	The best iteration of fitted model if <code>early_stopping()</code> callback has been specified.
<code>best_score_</code>	The best score of fitted model.
<code>booster_</code>	The underlying Booster of this model.
<code>classes_</code>	The class label array.
<code>evals_result_</code>	The evaluation results if validation sets have been specified.
<code>feature_importances_</code>	The feature importances (the higher, the more important).
<code>feature_name_</code>	The names of features.
<code>n_classes_</code>	The number of classes.
<code>n_estimators_</code>	True number of boosting iterations performed.
<code>n_features_</code>	The number of features of fitted model.
<code>n_features_in_</code>	The number of features of fitted model.
<code>n_iter_</code>	True number of boosting iterations performed.
<code>objective_</code>	The concrete objective used while fitting this model.

property `best_iteration_`

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type `int`

property `best_score_`

The best score of fitted model.

Type `dict`

property `booster_`

The underlying Booster of this model.

Type *Booster*

property `classes_`

The class label array.

Type `array` of shape = `[n_classes]`

property `evals_result_`

The evaluation results if validation sets have been specified.

Type `dict`

property feature_importances_

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

Note: `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type array of shape = [n_features]

property feature_name_

The names of features.

Type array of shape = [n_features]

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, *feature_name*='auto', *categorical_feature*='auto', *callbacks*=None, *init_model*=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 shape = [n_samples * n_classes] (for multi-class task) or shape = [n_samples, n_classes] (for multi-class task) or None, optional (default=None)) – Init score 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 str, or None, optional (default=None)) – Names of eval_set.
- **eval_sample_weight** (list of array, 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 array, or None, optional (default=None)) – Init score of eval data.
- **eval_metric** (str, callable, list or None, optional (default=None)) – If str, 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. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. 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.
- **feature_name** (list of str, or 'auto', optional (default='auto')) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.

- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, 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 callable, or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.
- **init_model** (*str, pathlib.Path, Booster, LGBMModel or None, optional (default=None)*) – Filename of LightGBM model, Booster instance or LGBMModel instance used for continue training.

Returns `self` – Returns self.

Return type `LGBMClassifier`

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. In case of custom `objective`, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight [numpy 1-D array of shape = [n_samples]] The weight of samples.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

eval_name [str] The name of evaluation function (without whitespace).

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

property n_classes_

The number of classes.

Type int

property n_estimators_

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type int

property n_features_

The number of features of fitted model.

Type int

property n_features_in_

The number of features of fitted model.

Type int

property n_iter_

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type int

property objective_

The concrete objective used while fitting this model.

Type str or callable

predict(*X*, *raw_score*=False, *start_iteration*=0, *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.
- **start_iteration** (int, optional (default=0)) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (int or None, optional (default=None)) – Total number of iterations used in the prediction. If None, if the best iteration exists and `start_iteration` <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` 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 = $[n_samples, (n_features + 1) * n_classes]$ or list with $n_classes$ length of such objects) – If `pred_contrib=True`, the feature contributions for each sample.

predict_proba(*X*, *raw_score=False*, *start_iteration=0*, *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.
- **start_iteration** (int, optional (default=0)) – Start index of the iteration to predict. If ≤ 0 , starts from the first iteration.
- **num_iteration** (int or None, optional (default=None)) – Total number of iterations used in the prediction. If None, if the best iteration exists and `start_iteration` ≤ 0 , the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If ≤ 0 , all iterations from `start_iteration` 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 = $[n_samples]$ 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 = $[n_samples, (n_features + 1) * n_classes]$ or list with $n_classes$ length of such objects) – 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(*args, **kwargs)

Bases: sklearn.base.RegressorMixin, [lightgbm.sklearn.LGBMModel](#)

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, importance_type='split', **kwargs)

Construct a gradient boosting model.

Parameters

- **boosting_type** (str, 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** (str, 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, 'lamdarank' 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, RandomState object or None, optional (default=None)*) – Random number seed. If `int`, this number is used to seed the C++ code. If `RandomState` object (numpy), a random integer is picked based on its state to seed the C++ code. If `None`, default seeds in C++ code are used.
- **n_jobs** (*int, optional (default=-1)*) – Number of parallel threads to use for training (can be changed at prediction time).
- **importance_type** (*str, 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.

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10

records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

grad [list, numpy 1-D array or pandas Series of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of y_pred for each sample point.

hess [list, numpy 1-D array or pandas Series of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of y_pred 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, start_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>	The best iteration of fitted model if <code>early_stopping()</code> callback has been specified.
<code>best_score_</code>	The best score of fitted model.
<code>booster_</code>	The underlying Booster of this model.
<code>evals_result_</code>	The evaluation results if validation sets have been specified.
<code>feature_importances_</code>	The feature importances (the higher, the more important).
<code>feature_name_</code>	The names of features.
<code>n_estimators_</code>	True number of boosting iterations performed.
<code>n_features_</code>	The number of features of fitted model.
<code>n_features_in_</code>	The number of features of fitted model.
<code>n_iter_</code>	True number of boosting iterations performed.
<code>objective_</code>	The concrete objective used while fitting this model.

property `best_iteration_`

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type int

property `best_score_`

The best score of fitted model.

Type dict

property `booster_`

The underlying Booster of this model.

Type *Booster*

property `evals_result_`

The evaluation results if validation sets have been specified.

Type dict

property `feature_importances_`

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

Note: `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type array of shape = [n_features]

property `feature_name_`

The names of features.

Type array of shape = [n_features]

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, feature_name='auto', categorical_feature='auto', callbacks=None, init_model=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 shape = [n_samples * n_classes] (for multi-class task) or shape = [n_samples, n_classes] (for multi-class task) or None, optional (default=None)) – Init score 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 str, or None, optional (default=None)) – Names of eval_set.
- **eval_sample_weight** (list of array, or None, optional (default=None)) – Weights of eval data.
- **eval_init_score** (list of array, or None, optional (default=None)) – Init score of eval data.
- **eval_metric** (str, callable, list or None, optional (default=None)) – If str, 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. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. 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.

- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, 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 callable, or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.
- **init_model** (*str, pathlib.Path, Booster, LGBMModel or None, optional (default=None)*) – Filename of LightGBM model, Booster instance or LGBMModel instance used for continue training.

Returns **self** – Returns self.

Return type *LGBMRegressor*

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. In case of custom **objective**, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight [numpy 1-D array of shape = [n_samples]] The weight of samples.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with **group** = [10, 20, 40, 10, 10, 10], that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

eval_name [str] The name of evaluation function (without whitespace).

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

property `n_estimators_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type int

property `n_features_`

The number of features of fitted model.

Type int

property `n_features_in_`

The number of features of fitted model.

Type int

property `n_iter_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type int

property `objective_`

The concrete objective used while fitting this model.

Type str or callable

predict (`X`, `raw_score=False`, `start_iteration=0`, `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.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If ≤ 0 , starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and `start_iteration` ≤ 0 , the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If ≤ 0 , all iterations from `start_iteration` 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 = $[n_samples, (n_features + 1) * n_classes]$ or list with $n_classes$ length of such objects) – 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(*args, **kwargs)

Bases: [lightgbm.sklearn.LGBMModel](#)

LightGBM ranker.

Warning: scikit-learn doesn't support ranking applications yet, therefore this class is not really compatible with the sklearn ecosystem. Please use this class mainly for training and applying ranking models in common sklearnish way.

__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, importance_type='split', **kwargs)

Construct a gradient boosting model.

Parameters

- **boosting_type** (str, 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** (*str, 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, RandomState object or None, optional (default=None)*) – Random number seed. If `int`, this number is used to seed the C++ code. If `RandomState` object (numpy), a random integer is picked based on its state to seed the C++ code. If `None`, default seeds in C++ code are used.
- **n_jobs** (*int, optional (default=-1)*) – Number of parallel threads to use for training (can be changed at prediction time).

- **importance_type** (*str, 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.

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

grad [list, numpy 1-D array or pandas Series of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of `y_pred` for each sample point.

hess [list, numpy 1-D array or pandas Series of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of `y_pred` 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, start_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>	The best iteration of fitted model if <code>early_stopping()</code> callback has been specified.
<code>best_score_</code>	The best score of fitted model.
<code>booster_</code>	The underlying Booster of this model.
<code>evals_result_</code>	The evaluation results if validation sets have been specified.
<code>feature_importances_</code>	The feature importances (the higher, the more important).
<code>feature_name_</code>	The names of features.
<code>n_estimators_</code>	True number of boosting iterations performed.
<code>n_features_</code>	The number of features of fitted model.
<code>n_features_in_</code>	The number of features of fitted model.
<code>n_iter_</code>	True number of boosting iterations performed.
<code>objective_</code>	The concrete objective used while fitting this model.

property `best_iteration_`

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type `int`

property `best_score_`

The best score of fitted model.

Type `dict`

property `booster_`

The underlying Booster of this model.

Type *Booster*

property `evals_result_`

The evaluation results if validation sets have been specified.

Type `dict`

property `feature_importances_`

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

Note: `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type `array` of shape = `[n_features]`

property `feature_name_`

The names of features.

Type `array` of shape = `[n_features]`

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, 2, 3, 4, 5)`, `feature_name='auto'`, `categorical_feature='auto'`, `callbacks=None`, `init_model=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 shape = $[n_samples * n_classes]$ (for multi-class task) or shape = $[n_samples, n_classes]$ (for multi-class task) or None, optional (default=None)) – Init score of training data.
- **group** (array-like or None, optional (default=None)) – Group/query data. Only used in the learning-to-rank task. $\text{sum}(\text{group}) = n_samples$. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
- **eval_set** (list or None, optional (default=None)) – A list of (X, y) tuple pairs to use as validation sets.
- **eval_names** (list of str, or None, optional (default=None)) – Names of eval_set.
- **eval_sample_weight** (list of array, or None, optional (default=None)) – Weights of eval data.
- **eval_init_score** (list of array, or None, optional (default=None)) – Init score of eval data.
- **eval_group** (list of array, or None, optional (default=None)) – Group data of eval data.
- **eval_metric** (str, callable, list or None, optional (default=None)) – If str, 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. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. 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** (iterable of int, optional (default=(1, 2, 3, 4, 5))) – The evaluation positions of the specified metric.
- **feature_name** (list of str, or 'auto', optional (default='auto')) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (list of str or int, or 'auto', optional (default='auto')) – Categorical features. If list of int, interpreted as indices. If list of str, 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 callable, or None, optional (default=None)) – List of callback functions that are applied at each iteration. See Callbacks in Python

API for more information.

- **init_model** (*str*, *pathlib.Path*, *Booster*, *LGBMModel* or *None*, *optional* (*default=None*)) – Filename of LightGBM model, Booster instance or LGBMModel instance used for continue training.

Returns *self* – Returns self.

Return type *LGBMRanker*

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. In case of custom *objective*, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight [numpy 1-D array of shape = [n_samples]] The weight of samples.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

eval_name [str] The name of evaluation function (without whitespace).

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

property *n_estimators_*

True number of boosting iterations performed.

This might be less than parameter *n_estimators* if early stopping was enabled or if boosting stopped early due to limits on complexity like *min_gain_to_split*.

Type int

property *n_features_*

The number of features of fitted model.

Type int

property *n_features_in_*

The number of features of fitted model.

Type `int`

property **n_iter_**

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type `int`

property **objective_**

The concrete objective used while fitting this model.

Type `str` or callable

predict(*X*, *raw_score=False*, *start_iteration=0*, *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.
- **start_iteration** (*int*, optional (default=0)) – Start index of the iteration to predict. If ≤ 0 , starts from the first iteration.
- **num_iteration** (*int* or *None*, optional (default=None)) – Total number of iterations used in the prediction. If *None*, if the best iteration exists and `start_iteration` ≤ 0 , the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If ≤ 0 , all iterations from `start_iteration` 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*] or list with *n_classes* length of such objects) – 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 Dask API

New in version 3.2.0.

<code>DaskLGBMClassifier(*args, **kwargs)</code>	Distributed version of <code>lightgbm.LGBMClassifier</code> .
<code>DaskLGBMRegressor(*args, **kwargs)</code>	Distributed version of <code>lightgbm.LGBMRegressor</code> .
<code>DaskLGBMRanker(*args, **kwargs)</code>	Distributed version of <code>lightgbm.LGBMRanker</code> .

9.4.1 `lightgbm.DaskLGBMClassifier`

class `lightgbm.DaskLGBMClassifier(*args, **kwargs)`

Bases: `lightgbm.sklearn.LGBMClassifier`, `lightgbm.dask._DaskLGBMModel`

Distributed version of `lightgbm.LGBMClassifier`.

__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_freq*=0, *colsample_bytree*=1.0, *reg_alpha*=0.0, *reg_lambda*=0.0, *random_state*=None, *n_jobs*=-1, *importance_type*='split', *client*=None, ****kwargs**)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str*, 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** (*str*, 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*, *RandomState* object or None, optional (default=None)) – Random number seed. If `int`, this number is used to seed the C++ code. If *RandomState* object (numpy), a random integer is picked based on its state to seed the C++ code. If None, default seeds in C++ code are used.
- **n_jobs** (*int*, optional (default=-1)) – Number of parallel threads to use for training (can be changed at prediction time).
- **importance_type** (*str*, 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.
- **client** (*dask.distributed.Client* or None, optional (default=None)) – Dask client. If None, `distributed.default_client()` will be used at runtime. The Dask client used by this class will not be saved if the model object is pickled.
- ****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.

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, **kwargs)</code>	Return the predicted value for each sample.
<code>predict_proba(X, **kwargs)</code>	Return the predicted probability for each class for each sample.
<code>set_params(**params)</code>	Set the parameters of this estimator.
<code>to_local()</code>	Create regular version of lightgbm.LGBMClassifier from the distributed version.

Attributes

<code>best_iteration_</code>	The best iteration of fitted model if <code>early_stopping()</code> callback has been specified.
<code>best_score_</code>	The best score of fitted model.
<code>booster_</code>	The underlying Booster of this model.
<code>classes_</code>	The class label array.
<code>client_</code>	Dask client.
<code>evals_result_</code>	The evaluation results if validation sets have been specified.
<code>feature_importances_</code>	The feature importances (the higher, the more important).
<code>feature_name_</code>	The names of features.
<code>n_classes_</code>	The number of classes.
<code>n_estimators_</code>	True number of boosting iterations performed.
<code>n_features_</code>	The number of features of fitted model.
<code>n_features_in_</code>	The number of features of fitted model.
<code>n_iter_</code>	True number of boosting iterations performed.
<code>objective_</code>	The concrete objective used while fitting this model.

property `best_iteration_`

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type `int`

property `best_score_`

The best score of fitted model.

Type `dict`

property `booster_`

The underlying Booster of this model.

Type `Booster`

property `classes_`

The class label array.

Type `array of shape = [n_classes]`

property `client_`

Dask client.

This property can be passed in the constructor or updated with `model.set_params(client=client)`.

Type `dask.distributed.Client`

property evals_result_

The evaluation results if validation sets have been specified.

Type `dict`

property feature_importances_

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

Note: `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type `array` of shape = `[n_features]`

property feature_name_

The names of features.

Type `array` of shape = `[n_features]`

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, ***kwargs*)

Build a gradient boosting model from the training set (*X*, *y*).

Parameters

- **X** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input feature matrix.
- **y** (*Dask Array, Dask DataFrame or Dask Series of shape = [n_samples]*) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (*Dask Array or Dask Series of shape = [n_samples] or None, optional (default=None)*) – Weights of training data.
- **init_score** (*Dask Array or Dask Series of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task), or Dask Array or Dask DataFrame of shape = [n_samples, n_classes] (for multi-class task), or None, optional (default=None)*) – Init score 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 str, or None, optional (default=None)*) – Names of *eval_set*.
- **eval_sample_weight** (*list of Dask Array or Dask Series, 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 Dask Array, Dask Series or Dask DataFrame (for multi-class task), or None, optional (default=None)*) – Init score of eval data.

- **eval_metric** (*str, callable, list or None, optional (default=None)*) – If *str*, 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. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. 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.
- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, 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.
- ****kwargs** – Other parameters passed through to `LGBMClassifier.fit()`.

Returns *self* – Returns self.

Return type *lightgbm.DaskLGBMClassifier*

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. In case of custom *objective*, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight [numpy 1-D array of shape = [n_samples]] The weight of samples.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

eval_name [str] The name of evaluation function (without whitespace).

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

property `n_classes_`

The number of classes.

Type int

property `n_estimators_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type int

property `n_features_`

The number of features of fitted model.

Type int

property `n_features_in_`

The number of features of fitted model.

Type int

property `n_iter_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type int

property `objective_`

The concrete objective used while fitting this model.

Type str or callable

predict(`X`, ***kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If ≤ 0 , starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and `start_iteration` ≤ 0 , the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If ≤ 0 , all iterations from `start_iteration` 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** (Dask Array of shape = $[n_samples]$ or shape = $[n_samples, n_classes]$) – The predicted values.
- **X_leaves** (Dask Array 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** (Dask Array of shape = $[n_samples, n_features + 1]$ or shape = $[n_samples, (n_features + 1) * n_classes]$ or (if multi-class and using sparse inputs) a list of `n_classes` Dask Arrays of shape = $[n_samples, n_features + 1]$) – If `pred_contrib=True`, the feature contributions for each sample.

predict_proba(X, **kwargs)

Return the predicted probability for each class for each sample.

Parameters

- **X** (Dask Array or Dask DataFrame of shape = $[n_samples, n_features]$) – Input features matrix.
- **raw_score** (bool, optional (default=False)) – Whether to predict raw scores.
- **start_iteration** (int, optional (default=0)) – Start index of the iteration to predict. If ≤ 0 , starts from the first iteration.
- **num_iteration** (int or None, optional (default=None)) – Total number of iterations used in the prediction. If None, if the best iteration exists and `start_iteration` ≤ 0 , the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If ≤ 0 , all iterations from `start_iteration` 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** (Dask Array of shape = $[n_samples]$ or shape = $[n_samples, n_classes]$) – The predicted values.

- **X_leaves** (Dask Array 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** (Dask Array of shape = $[n_samples, n_features + 1]$ or shape = $[n_samples, (n_features + 1) * n_classes]$ or (if multi-class and using sparse inputs) a list of `n_classes` Dask Arrays of shape = $[n_samples, n_features + 1]$) – 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

to_local()

Create regular version of `lightgbm.LGBMClassifier` from the distributed version.

Returns **model** – Local underlying model.

Return type `lightgbm.LGBMClassifier`

9.4.2 lightgbm.DaskLGBMRegressor

class `lightgbm.DaskLGBMRegressor(*args, **kwargs)`

Bases: `lightgbm.sklearn.LGBMRegressor`, `lightgbm.dask._DaskLGBMModel`

Distributed version of `lightgbm.LGBMRegressor`.

__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, importance_type='split', client=None, **kwargs*)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str, 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** (*str, 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, RandomState object or None, optional (default=None)*) – Random number seed. If `int`, this number is used to seed the C++ code. If `RandomState` object (numpy), a random integer is picked based on its state to seed the C++ code. If `None`, default seeds in C++ code are used.
- **n_jobs** (*int, optional (default=-1)*) – Number of parallel threads to use for training (can be changed at prediction time).
- **importance_type** (*str, 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.
- **client** (*dask.distributed.Client or None, optional (default=None)*) – Dask client. If `None`, `distributed.default_client()` will be used at runtime. The Dask client used by this class will not be saved if the model object is pickled.
- ****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.

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, **kwargs)</code>	Return the predicted value for each sample.
<code>set_params(**params)</code>	Set the parameters of this estimator.
<code>to_local()</code>	Create regular version of <code>lightgbm.LGBMRegressor</code> from the distributed version.

Attributes

<code>best_iteration_</code>	The best iteration of fitted model if <code>early_stopping()</code> callback has been specified.
<code>best_score_</code>	The best score of fitted model.
<code>booster_</code>	The underlying Booster of this model.
<code>client_</code>	Dask client.
<code>evals_result_</code>	The evaluation results if validation sets have been specified.
<code>feature_importances_</code>	The feature importances (the higher, the more important).
<code>feature_name_</code>	The names of features.
<code>n_estimators_</code>	True number of boosting iterations performed.
<code>n_features_</code>	The number of features of fitted model.
<code>n_features_in_</code>	The number of features of fitted model.
<code>n_iter_</code>	True number of boosting iterations performed.
<code>objective_</code>	The concrete objective used while fitting this model.

property `best_iteration_`

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type `int`

property `best_score_`

The best score of fitted model.

Type `dict`

property `booster_`

The underlying Booster of this model.

Type `Booster`

property `client_`

Dask client.

This property can be passed in the constructor or updated with `model.set_params(client=client)`.

Type `dask.distributed.Client`

property evals_result_

The evaluation results if validation sets have been specified.

Type dict

property feature_importances_

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

Note: `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type array of shape = `[n_features]`

property feature_name_

The names of features.

Type array of shape = `[n_features]`

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, ***kwargs*)
Build a gradient boosting model from the training set (*X*, *y*).

Parameters

- **X** (Dask Array or Dask DataFrame of shape = `[n_samples, n_features]`) – Input feature matrix.
- **y** (Dask Array, Dask DataFrame or Dask Series of shape = `[n_samples]`) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (Dask Array or Dask Series of shape = `[n_samples]` or None, optional (default=None)) – Weights of training data.
- **init_score** (Dask Array or Dask Series of shape = `[n_samples]` or None, optional (default=None)) – Init score 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 str, or None, optional (default=None)) – Names of *eval_set*.
- **eval_sample_weight** (list of Dask Array or Dask Series, or None, optional (default=None)) – Weights of eval data.
- **eval_init_score** (list of Dask Array or Dask Series, or None, optional (default=None)) – Init score of eval data.
- **eval_metric** (str, callable, list or None, optional (default=None)) – If str, 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. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. 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.
- **feature_name** (list of str, or 'auto', optional (default='auto')) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.

- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, 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.
- ****kwargs** – Other parameters passed through to `LGBMRegressor.fit()`.

Returns `self` – Returns self.

Return type `lightgbm.DaskLGBMRegressor`

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. In case of custom `objective`, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight [numpy 1-D array of shape = [n_samples]] The weight of samples.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

eval_name [str] The name of evaluation function (without whitespace).

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

property `n_estimators_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type int

property n_features_

The number of features of fitted model.

Type int

property n_features_in_

The number of features of fitted model.

Type int

property n_iter_

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type int

property objective_

The concrete objective used while fitting this model.

Type str or callable

predict(X, **kwargs)

Return the predicted value for each sample.

Parameters

- **X** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If ≤ 0 , starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and `start_iteration` ≤ 0 , the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If ≤ 0 , all iterations from `start_iteration` 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** (*Dask Array of shape = [n_samples]*) – The predicted values.
- **X_leaves** (*Dask Array of shape = [n_samples, n_trees]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*Dask Array of shape = [n_samples, n_features + 1]*) – 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

to_local()

Create regular version of lightgbm.LGBMRegressor from the distributed version.

Returns **model** – Local underlying model.

Return type *lightgbm.LGBMRegressor*

9.4.3 lightgbm.DaskLGBMRanker

class lightgbm.DaskLGBMRanker(*args, **kwargs)

Bases: *lightgbm.sklearn.LGBMRanker*, *lightgbm.dask._DaskLGBMModel*

Distributed version of lightgbm.LGBMRanker.

__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, importance_type='split', client=None, **kwargs*)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str, 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** (*str, 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, RandomState object or None, optional (default=None)*) – Random number seed. If `int`, this number is used to seed the C++ code. If `RandomState` object (numpy), a random integer is picked based on its state to seed the C++ code. If `None`, default seeds in C++ code are used.
- **n_jobs** (*int, optional (default=-1)*) – Number of parallel threads to use for training (can be changed at prediction time).
- **importance_type** (*str, 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.
- **client** (*dask.distributed.Client or None, optional (default=None)*) – Dask client. If `None`, `distributed.default_client()` will be used at runtime. The Dask client used by this class will not be saved if the model object is pickled.
- ****kwargs** – Other parameters for the model. Check <http://lightgbm.readthedocs.io/en/latest/Parameters.html> for more parameters.

Warning: <code>**kwargs</code> is not supported in sklearn, it may cause unexpected issues.
--

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, **kwargs)</code>	Return the predicted value for each sample.
<code>set_params(**params)</code>	Set the parameters of this estimator.
<code>to_local()</code>	Create regular version of lightgbm.LGBMRanker from the distributed version.

Attributes

<code>best_iteration_</code>	The best iteration of fitted model if <code>early_stopping()</code> callback has been specified.
<code>best_score_</code>	The best score of fitted model.
<code>booster_</code>	The underlying Booster of this model.
<code>client_</code>	Dask client.
<code>evals_result_</code>	The evaluation results if validation sets have been specified.
<code>feature_importances_</code>	The feature importances (the higher, the more important).
<code>feature_name_</code>	The names of features.
<code>n_estimators_</code>	True number of boosting iterations performed.
<code>n_features_</code>	The number of features of fitted model.
<code>n_features_in_</code>	The number of features of fitted model.
<code>n_iter_</code>	True number of boosting iterations performed.
<code>objective_</code>	The concrete objective used while fitting this model.

property `best_iteration_`

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type `int`

property `best_score_`

The best score of fitted model.

Type `dict`

property `booster_`

The underlying Booster of this model.

Type *Booster*

property `client_`

Dask client.

This property can be passed in the constructor or updated with `model.set_params(client=client)`.

Type `dask.distributed.Client`

property `evals_result_`

The evaluation results if validation sets have been specified.

Type `dict`

property feature_importances_

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

Note: `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type array of shape = [n_features]

property feature_name_

The names of features.

Type array of shape = [n_features]

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, 2, 3, 4, 5), **kwargs)

Build a gradient boosting model from the training set (X, y).

Parameters

- **X** (Dask Array or Dask DataFrame of shape = [n_samples, n_features]) – Input feature matrix.
- **y** (Dask Array, Dask DataFrame or Dask Series of shape = [n_samples]) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (Dask Array or Dask Series of shape = [n_samples] or None, optional (default=None)) – Weights of training data.
- **init_score** (Dask Array or Dask Series of shape = [n_samples] or None, optional (default=None)) – Init score of training data.
- **group** (Dask Array or Dask Series or None, optional (default=None)) – Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
- **eval_set** (list or None, optional (default=None)) – A list of (X, y) tuple pairs to use as validation sets.
- **eval_names** (list of str, or None, optional (default=None)) – Names of eval_set.
- **eval_sample_weight** (list of Dask Array or Dask Series, or None, optional (default=None)) – Weights of eval data.
- **eval_init_score** (list of Dask Array or Dask Series, or None, optional (default=None)) – Init score of eval data.
- **eval_group** (list of Dask Array or Dask Series, or None, optional (default=None)) – Group data of eval data.
- **eval_metric** (str, callable, list or None, optional (default=None)) – If str, 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. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix

of both. 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** (*iterable of int, optional (default=(1, 2, 3, 4, 5))*) – The evaluation positions of the specified metric.
- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, 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.
- ****kwargs** – Other parameters passed through to `LGBMRanker.fit()`.

Returns `self` – Returns self.

Return type `lightgbm.DaskLGBMRanker`

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 [numpy 1-D array of shape = [n_samples]] The target values.

y_pred [numpy 1-D array of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task)] The predicted values. In case of custom `objective`, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight [numpy 1-D array of shape = [n_samples]] The weight of samples.

group [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. `sum(group) = n_samples`. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

eval_name [str] The name of evaluation function (without whitespace).

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

property `n_estimators_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type int

property `n_features_`

The number of features of fitted model.

Type int

property `n_features_in_`

The number of features of fitted model.

Type int

property `n_iter_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Type int

property `objective_`

The concrete objective used while fitting this model.

Type str or callable

`predict(X, **kwargs)`

Return the predicted value for each sample.

Parameters

- **`X`** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input features matrix.
- **`raw_score`** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **`start_iteration`** (*int, optional (default=0)*) – Start index of the iteration to predict. If ≤ 0 , starts from the first iteration.
- **`num_iteration`** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and `start_iteration` ≤ 0 , the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If ≤ 0 , all iterations from `start_iteration` 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** (*Dask Array of shape = [n_samples]*) – The predicted values.
- **X_leaves** (*Dask Array of shape = [n_samples, n_trees]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*Dask Array of shape = [n_samples, n_features + 1]*) – 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

to_local()

Create regular version of `lightgbm.LGBMRanker` from the distributed version.

Returns **model** – Local underlying model.

Return type *lightgbm.LGBMRanker*

9.5 Callbacks

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

9.5.1 lightgbm.early_stopping

lightgbm.early_stopping(stopping_rounds, first_metric_only=False, verbose=True, min_delta=0.0)

Create a callback that activates early stopping.

Activates early stopping. The model will train until the validation score doesn't improve by at least `min_delta`. Validation score needs to improve at least every `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`. The index of iteration that has the best performance will be saved in the `best_iteration` attribute of a model.

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 log message with early stopping information. By default, standard output resource is used. Use `register_logger()` function to register a custom logger.

- **min_delta** (*float or list of float, optional (default=0.0)*) – Minimum improvement in score to keep training. If float, this single value is used for all metrics. If list, its length should match the total number of metrics.

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

Return type callable

9.5.2 lightgbm.log_evaluation

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

Create a callback that logs the evaluation results.

By default, standard output resource is used. Use `register_logger()` function to register a custom logger.

Note: Requires at least one validation data.

Parameters

- **period** (*int, optional (default=1)*) – The period to log the evaluation results. The last boosting stage or the boosting stage found by using `early_stopping` callback is also logged.
- **show_stdv** (*bool, optional (default=True)*) – Whether to log stdv (if provided).

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

Return type callable

9.5.3 lightgbm.record_evaluation

`lightgbm.record_evaluation(eval_result)`

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

Parameters **eval_result** (*dict*) – Dictionary used to store all evaluation results of all validation sets. This should be initialized outside of your call to `record_evaluation()` and should be empty. Any initial contents of the dictionary will be deleted.

Example

With two validation sets named ‘eval’ and ‘train’, and one evaluation metric named ‘logloss’ this dictionary after finishing a model training process will have the following structure:

```
{
  'train':
    {
      'logloss': [0.48253, 0.35953, ...]
    },
  'eval':
    {
      'logloss': [0.480385, 0.357756, ...]
    }
}
```

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

Return type callable

9.5.4 `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 callable*) – List of parameters for each boosting round or a callable 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 callable `func`, `parameter = func(current_round)`.

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

Return type callable

9.6 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.

9.6.1 `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='auto', 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** (*str or None, optional (default="Feature importance")*) – Axes title. If None, title is disabled.
- **xlabel** (*str or None, optional (default="Feature importance")*) – X-axis title label. If None, title is disabled. @importance_type@ placeholder can be used, and it will be replaced with the value of importance_type parameter.
- **ylabel** (*str or None, optional (default="Features")*) – Y-axis title label. If None, title is disabled.
- **importance_type** (*str, optional (default="auto")*) – How the importance is calculated. If “auto”, if booster parameter is LGBMModel, booster.importance_type attribute is used; “split” otherwise. 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`

9.6.2 `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 str*) – The feature name or index the histogram is plotted for. If int, interpreted as index. If str, interpreted as name.
- **bins** (*int, str or None, optional (default=None)*) – The maximum number of bins. If None, the number of bins equals number of unique split values. If str, 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** (*str 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 `str` type `feature` parameter.
- **xlabel** (*str or None, optional (default="Feature split value")*) – X-axis title label. If None, title is disabled.
- **ylabel** (*str 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`

9.6.3 `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='@metric@', 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** (*str 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 str, 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** (*str or None, optional (default="Metric during training")*) – Axes title. If None, title is disabled.
- **xlabel** (*str or None, optional (default="Iterations")*) – X-axis title label. If None, title is disabled.
- **ylabel** (*str or None, optional (default="@metric@")*) – Y-axis title label. If 'auto', metric name is used. If None, title is disabled. @metric@ placeholder can be used, and it will be replaced with metric name.
- **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

9.6.4 lightgbm.plot_tree

`lightgbm.plot_tree(booster, ax=None, tree_index=0, figsize=None, dpi=None, show_info=None, precision=3, orientation='horizontal', **kwargs)`

Plot specified tree.

Each node in the graph represents a node in the tree.

Non-leaf nodes have labels like `Column_10 <= 875.9`, which means “this node splits on the feature named “Column_10”, with threshold 875.9”.

Leaf nodes have labels like `leaf 2: 0.422`, which means “this node is a leaf node, and the predicted value for records that fall into this node is 0.422”. The number (2) is an internal unique identifier and doesn't have any special meaning.

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 str, or None, optional (default=None)*) – What information should be shown in nodes.
 - 'split_gain' : gain from adding this split to the model
 - 'internal_value' : raw predicted value that would be produced by this node if it was a leaf node

- 'internal_count' : number of records from the training data that fall into this non-leaf node
- 'internal_weight' : total weight of all nodes that fall into this non-leaf node
- 'leaf_count' : number of records from the training data that fall into this leaf node
- 'leaf_weight' : total weight (sum of hessian) of all observations that fall into this leaf node
- 'data_percentage' : percentage of training data that fall into this node
- **precision** (*int or None, optional (default=3)*) – Used to restrict the display of floating point values to a certain precision.
- **orientation** (*str, optional (default='horizontal')*) – Orientation of the tree. Can be 'horizontal' or 'vertical'.
- ****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`

9.6.5 lightgbm.create_tree_digraph

`lightgbm.create_tree_digraph(booster, tree_index=0, show_info=None, precision=3, orientation='horizontal', **kwargs)`

Create a digraph representation of specified tree.

Each node in the graph represents a node in the tree.

Non-leaf nodes have labels like `Column_10 <= 875.9`, which means “this node splits on the feature named “Column_10”, with threshold 875.9”.

Leaf nodes have labels like `leaf 2: 0.422`, which means “this node is a leaf node, and the predicted value for records that fall into this node is 0.422”. The number (2) is an internal unique identifier and doesn’t have any special meaning.

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 str, or None, optional (default=None)*) – What information should be shown in nodes.
 - 'split_gain' : gain from adding this split to the model
 - 'internal_value' : raw predicted value that would be produced by this node if it was a leaf node
 - 'internal_count' : number of records from the training data that fall into this non-leaf node
 - 'internal_weight' : total weight of all nodes that fall into this non-leaf node

- 'leaf_count' : number of records from the training data that fall into this leaf node
- 'leaf_weight' : total weight (sum of hessian) of all observations that fall into this leaf node
- 'data_percentage' : percentage of training data that fall into this node
- **precision** (*int or None, optional (default=3)*) – Used to restrict the display of floating point values to a certain precision.
- **orientation** (*str, optional (default='horizontal')*) – Orientation of the tree. Can be 'horizontal' or 'vertical'.
- ****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

9.7 Utilities

register_logger(logger)

Register custom logger.

9.7.1 lightgbm.register_logger

lightgbm.**register_logger**(*logger*)

Register custom logger.

Parameters **logger** (*logging.Logger*) – Custom logger.

DISTRIBUTED LEARNING GUIDE

This guide describes distributed learning in LightGBM. Distributed learning allows the use of multiple machines to produce a single model.

Follow the [Quick Start](#) to know how to use LightGBM first.

10.1 How Distributed LightGBM Works

This section describes how distributed learning in LightGBM works. To learn how to do this in various programming languages and frameworks, please see [Integrations](#).

10.1.1 Choose Appropriate Parallel Algorithm

LightGBM provides 3 distributed 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 distributed learning](#).

10.2 Integrations

This section describes how to run distributed LightGBM training in various programming languages and frameworks. To learn how distributed learning in LightGBM works generally, please see [How Distributed LightGBM Works](#).

10.2.1 Apache Spark

Apache Spark users can use [SynapseML](#) for machine learning workflows with LightGBM. This project is not maintained by LightGBM's maintainers.

See [this SynapseML example](#) for additional information on using LightGBM on Spark.

Note: SynapseML is not maintained by LightGBM's maintainers. Bug reports or feature requests should be directed to <https://github.com/microsoft/SynapseML/issues>.

10.2.2 Dask

New in version 3.2.0.

LightGBM's Python package supports distributed learning via [Dask](#). This integration is maintained by LightGBM's maintainers.

Warning: Dask integration is only tested on Linux.

Dask Examples

For sample code using `lightgbm.dask`, see [these Dask examples](#).

Training with Dask

This section contains detailed information on performing LightGBM distributed training using Dask.

Configuring the Dask Cluster

Allocating Threads

When setting up a Dask cluster for training, give each Dask worker process at least two threads. If you do not do this, training might be substantially slower because communication work and training work will block each other.

If you do not have other significant processes competing with Dask for resources, just accept the default `nthreads` from your chosen `dask.distributed` cluster.

```
from distributed import Client, LocalCluster

cluster = LocalCluster(n_workers=3)
client = Client(cluster)
```

Managing Memory

Use the Dask diagnostic dashboard or your preferred monitoring tool to monitor Dask workers' memory consumption during training. As described in [the Dask worker documentation](#), Dask workers will automatically start spilling data to disk if memory consumption gets too high. This can substantially slow down computations, since disk I/O is usually much slower than reading the same data from memory.

At 60% of memory load, [Dask will] spill least recently used data to disk

To reduce the risk of hitting memory limits, consider restarting each worker process before running any data loading or training code.

```
client.restart()
```

Setting Up Training Data

The estimators in `lightgbm.dask` expect that matrix-like or array-like data are provided in Dask DataFrame, Dask Array, or (in some cases) Dask Series format. See [the Dask DataFrame documentation](#) and [the Dask Array documentation](#) for more information on how to create such data structures.

While setting up for training, `lightgbm` will concatenate all of the partitions on a worker into a single dataset. Distributed training then proceeds with one LightGBM worker process per Dask worker.

When setting up data partitioning for LightGBM training with Dask, try to follow these suggestions:

- ensure that each worker in the cluster has some of the training data
- try to give each worker roughly the same amount of data, especially if your dataset is small
- if you plan to train multiple models (for example, to tune hyperparameters) on the same data, use `client.persist()` before training to materialize the data one time

Using a Specific Dask Client

In most situations, you should not need to tell `lightgbm.dask` to use a specific Dask client. By default, the client returned by `distributed.default_client()` will be used.

However, you might want to explicitly control the Dask client used by LightGBM if you have multiple active clients in the same session. This is useful in more complex workflows like running multiple training jobs on different Dask clusters.

LightGBM's Dask estimators support setting an attribute `client` to control the client that is used.

```
import lightgbm as lgb
from distributed import Client, LocalCluster

cluster = LocalCluster()
client = Client(cluster)

# option 1: keyword argument in constructor
dask_model = lgb.DaskLGBMClassifier(client=client)

# option 2: set_params() after construction
dask_model = lgb.DaskLGBMClassifier()
dask_model.set_params(client=client)
```

Using Specific Ports

At the beginning of training, `lightgbm.dask` sets up a LightGBM network where each Dask worker runs one long-running task that acts as a LightGBM worker. During training, LightGBM workers communicate with each other over TCP sockets. By default, random open ports are used when creating these sockets.

If the communication between Dask workers in the cluster used for training is restricted by firewall rules, you must tell LightGBM exactly what ports to use.

Option 1: provide a specific list of addresses and ports

LightGBM supports a parameter `machines`, a comma-delimited string where each entry refers to one worker (host name or IP) and a port that that worker will accept connections on. If you provide this parameter to the estimators in `lightgbm.dask`, LightGBM will not search randomly for ports.

For example, consider the case where you are running one Dask worker process on each of the following IP addresses:

```
10.0.1.0
10.0.2.0
10.0.3.0
```

You could edit your firewall rules to allow traffic on one additional port on each of these hosts, then provide `machines` directly.

```
import lightgbm as lgb

machines = "10.0.1.0:12401,10.0.2.0:12402,10.0.3.0:15000"
dask_model = lgb.DaskLGBMRegressor(machines=machines)
```

If you are running multiple Dask worker processes on physical host in the cluster, be sure that there are multiple entries for that IP address, with different ports. For example, if you were running a cluster with `nprocs=2` (2 Dask worker processes per machine), you might open two additional ports on each of these hosts, then provide `machines` as follows.

```
import lightgbm as lgb

machines = ",".join([
    "10.0.1.0:16000",
    "10.0.1.0:16001",
    "10.0.2.0:16000",
    "10.0.2.0:16001",
])
dask_model = lgb.DaskLGBMRegressor(machines=machines)
```

Warning: Providing `machines` gives you complete control over the networking details of training, but it also makes the training process fragile. Training will fail if you use `machines` and any of the following are true:

- any of the ports mentioned in `machines` are not open when training begins
- some partitions of the training data are held by machines that are not present in `machines`
- some machines mentioned in `machines` do not hold any of the training data

Option 2: specify one port to use on every worker

If you are only running one Dask worker process on each host, and if you can reliably identify a port that is open on every host, using `machines` is unnecessarily complicated. If `local_listen_port` is given and `machines` is not,

LightGBM will not search for ports randomly, but it will limit the list of addresses in the LightGBM network to those Dask workers that have a piece of the training data.

For example, consider the case where you are running one Dask worker process on each of the following IP addresses:

```
10.0.1.0
10.0.2.0
10.0.3.0
```

You could edit your firewall rules to allow communication between any of the workers over one port, then provide that port via parameter `local_listen_port`.

```
import lightgbm as lgb

dask_model = lgb.DaskLGBMRegressor(local_listen_port=12400)
```

Warning: Providing `local_listen_port` is slightly less fragile than machines because LightGBM will automatically figure out which workers have pieces of the training data. However, using this method, training can fail if any of the following are true:

- the port `local_listen_port` is not open on any of the worker hosts
- any machine has multiple Dask worker processes running on it

Prediction with Dask

The estimators from `lightgbm.dask` can be used to create predictions based on data stored in Dask collections. In that interface, `.predict()` expects a Dask Array or Dask DataFrame, and returns a Dask Array of predictions.

See [the Dask prediction example](#) for some sample code that shows how to perform Dask-based prediction.

For model evaluation, consider using [the metrics functions from dask-ml](#). Those functions are intended to provide the same API as equivalent functions in `sklearn.metrics`, but they use distributed computation powered by Dask to compute metrics without all of the input data ever needing to be on a single machine.

Saving Dask Models

After training with Dask, you have several options for saving a fitted model.

Option 1: pickle the Dask estimator

LightGBM's Dask estimators can be pickled directly with `cloudpickle`, `joblib`, or `pickle`.

```
import dask.array as da
import pickle
import lightgbm as lgb
from distributed import Client, LocalCluster

cluster = LocalCluster(n_workers=2)
client = Client(cluster)

X = da.random.random((1000, 10), (500, 10))
y = da.random.random((1000,), (500,))
```

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```
dask_model = lgb.DaskLGBMRegressor()
dask_model.fit(X, y)

with open("dask-model.pkl", "wb") as f:
    pickle.dump(dask_model, f)
```

A model saved this way can then later be loaded with whichever serialization library you used to save it.

```
import pickle
with open("dask-model.pkl", "rb") as f:
    dask_model = pickle.load(f)
```

Note: If you explicitly set a Dask client (see *Using a Specific Dask Client*), it will not be saved when pickling the estimator. When loading a Dask estimator from disk, if you need to use a specific client you can add it after loading with `dask_model.set_params(client=client)`.

Option 2: pickle the sklearn estimator

The estimators available from `lightgbm.dask` can be converted to an instance of the equivalent class from `lightgbm.sklearn`. Choosing this option allows you to use Dask for training but avoid depending on any Dask libraries at scoring time.

```
import dask.array as da
import joblib
import lightgbm as lgb
from distributed import Client, LocalCluster

cluster = LocalCluster(n_workers=2)
client = Client(cluster)

X = da.random.random((1000, 10), (500, 10))
y = da.random.random((1000,), (500,))

dask_model = lgb.DaskLGBMRegressor()
dask_model.fit(X, y)

# convert to sklearn equivalent
sklearn_model = dask_model.to_local()

print(type(sklearn_model))
#> lightgbm.sklearn.LGBMRegressor

joblib.dump(sklearn_model, "sklearn-model.joblib")
```

A model saved this way can then later be loaded with whichever serialization library you used to save it.

```
import joblib

sklearn_model = joblib.load("sklearn-model.joblib")
```

Option 3: save the LightGBM Booster

The lowest-level model object in LightGBM is the `lightgbm.Booster`. After training, you can extract a Booster from the Dask estimator.

```
import dask.array as da
import lightgbm as lgb
from distributed import Client, LocalCluster

cluster = LocalCluster(n_workers=2)
client = Client(cluster)

X = da.random.random((1000, 10), (500, 10))
y = da.random.random((1000,), (500,))

dask_model = lgb.DaskLGBMRegressor()
dask_model.fit(X, y)

# get underlying Booster object
bst = dask_model.booster_
```

From the point forward, you can use any of the following methods to save the Booster:

- serialize with `cloudpickle`, `joblib`, or `pickle`
- `bst.dump_model()`: dump the model to a dictionary which could be written out as JSON
- `bst.model_to_string()`: dump the model to a string in memory
- `bst.save_model()`: write the output of `bst.model_to_string()` to a text file

10.2.3 Kubeflow

[Kubeflow Fairing](#) supports LightGBM distributed training. [These examples](#) show how to get started with LightGBM and Kubeflow Fairing in a hybrid cloud environment.

Kubeflow users can also use the [Kubeflow XGBoost Operator](#) for machine learning workflows with LightGBM. You can see [this example](#) for more details.

Kubeflow integrations for LightGBM are not maintained by LightGBM's maintainers.

Note: The Kubeflow integrations for LightGBM are not maintained by LightGBM's maintainers. Bug reports or feature requests should be directed to <https://github.com/kubeflow/fairing/issues> or <https://github.com/kubeflow/xgboost-operator/issues>.

10.2.4 LightGBM CLI

Preparation

By default, distributed learning with LightGBM uses socket-based communication.

If you need to build distributed version with MPI support, please refer to [Installation Guide](#).

Socket Version

It needs to collect IP of all machines that want to run distributed 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 `m1ist.txt`), like following:

```
machine1_ip 12345
machine2_ip 12345
```

MPI Version

It needs to collect IP (or hostname) of all machines that want to run distributed learning in. Then write these IP in one file (assume `m1ist.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](#).

Run Distributed Learning

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=m1ist.txt`, `m1ist.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 `m1ist.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`

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 `m1ist.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
```

Example

- A simple distributed learning example

10.2.5 Ray

Ray is a Python-based framework for distributed computing. The `lightgbm_ray` project, maintained within the official Ray GitHub organization, can be used to perform distributed LightGBM training using ray.

See the [lightgbm_ray documentation](#) for usage examples.

Note: `lightgbm_ray` is not maintained by LightGBM's maintainers. Bug reports or feature requests should be directed to https://github.com/ray-project/lightgbm_ray/issues.

10.2.6 Mars

Mars is a tensor-based framework for large-scale data computation. LightGBM integration, maintained within the Mars GitHub repository, can be used to perform distributed LightGBM training using `pymars`.

See the [mars documentation](#) for usage examples.

Note: `Mars` is not maintained by LightGBM's maintainers. Bug reports or feature requests should be directed to <https://github.com/mars-project/mars/issues>.

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/treelearner/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
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.

ADVANCED TOPICS

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 unrecorded values in sparse matrices (and LightSVM) are treated as zeros.
- When `zero_as_missing=true`, NA and zeros (including unrecorded 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 `lambdarank_truncation_level` to truncate the max DCG.

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 Distributed Learning

- Refer to [Distributed 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 FAQ

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)
- [@shiyu1994](#) **Yu Shi** (C++ code / Python-package)
- [@btrotta](#) **Belinda Trotta** (C++ code)
- [@Laurae2](#) **Damien Soukhavong** (R-package)
- [@jameslamb](#) **James Lamb** (R-package / Dask-package)
- [@jmoralez](#) **José Morales** (Dask-package)
- [@wxchan](#) **Wenxuan Chen** (Python-package)
- [@henry0312](#) **Tsukasa Omoto** (Python-package)
- [@StrikerRUS](#) **Nikita Titov** (Python-package)
- [@huanzhang12](#) **Huan Zhang** (GPU support)
- [@tongwu-msft](#) **Tong Wu** (C++ code / Python-package)
- [@hzy46](#) **Zhiyuan He** (C++ code / Python-package)

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?*
- *14. Why CMake cannot find the compiler when compiling LightGBM with MinGW?*
- *15. Where can I find LightGBM's logo to use it in my presentation?*

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](#).

Starting from [#2804](#) bagging result doesn't depend on the number of threads. So this issue should be solved in the latest version.

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).

Cloud platform container services may cause LightGBM to hang, if they use Linux fork to run multiple containers on a single instance. For example, LightGBM hangs in AWS Batch array jobs, which [use the ECS agent](#) to manage multiple running jobs. Setting `nthreads=1` mitigates the issue.

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.

13.2.14 14. Why CMake cannot find the compiler when compiling LightGBM with MinGW?

```
CMake Error: CMAKE_C_COMPILER not set, after EnableLanguage
CMake Error: CMAKE_CXX_COMPILER not set, after EnableLanguage
```

This is a known issue of CMake when using MinGW. The easiest solution is to run again your `cmake` command to bypass the one time stopper from CMake. Or you can upgrade your version of CMake to at least version 3.17.0.

See [Microsoft/LightGBM#3060](#) for more details.

13.2.15 15. Where can I find LightGBM's logo to use it in my presentation?

You can find LightGBM's logo in different file formats and resolutions [here](#).

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!*
- *3. error in `data.table::data.table()...` argument 2 is NULL*

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!

As of at least LightGBM v3.3.0, this issue has been resolved and printing a `Dataset` object does not cause the console to freeze.

In older versions, avoid printing the `Dataset` after calling `setinfo()`.

As of LightGBM v4.0.0, `setinfo()` has been replaced by a new method, `set_field()`.

13.3.3 3. error in `data.table::data.table()...` argument 2 is NULL

If you are experiencing this error when running `lightgbm`, you may be facing the same issue reported in [#2715](#) and later in [#2989](#). We have seen that some in some situations, using `data.table` 1.11.x results in this error. To get around this, you can upgrade your version of `data.table` to at least version 1.12.0.

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 get `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.

DEVELOPMENT GUIDE

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
FeatureGroup	Stores the data of feature, could be multiple features
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
./include	Header files
./include/utils	Some common functions
./src/application	Implementations of training and prediction logic
./src/boosting	Implementations of Boosting
./src/io	Implementations of IO related classes, including Bin, Config, Dataset, DatasetLoader, Feature and Tree
./src/metric	Implementations of metrics
./src/network	Implementations of network functions
./src/objective	Implementations of objective functions
./src/treelerner	Implementations of tree learners

14.3 Documents API

Refer to [docs README](#).

14.4 C API

Refer to [C API](#) or the comments in `c_api.h` file, from which the documentation is generated.

14.5 Tests

C++ unit tests are located in the `./tests/cpp_tests` folder and written with the help of Google Test framework. To run tests locally first refer to the [Installation Guide](#) for how to build tests and then simply run compiled executable file. It is highly recommended to build tests with [sanitizers](#).

14.6 High Level Language Package

See the implementations at [Python-package](#) and [R-package](#).

14.7 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. If you have categorical features, use the `categorical_column` option and input them into LightGBM directly; do not convert them into one-hot variables.

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	#Examples	#Features	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
device = gpu
```

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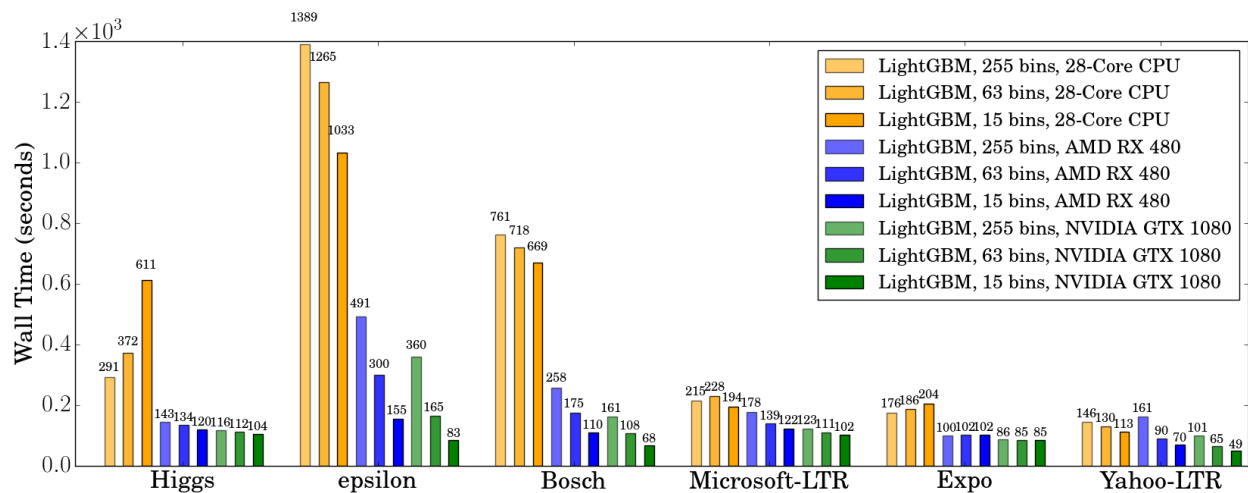
```
gpu_platform_id = 0
gpu_device_id = 0
num_thread = 28
```

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 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 from our GitHub repo ([for Linux](#) and [for Windows](#)).

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,
+               num_tree_per_iteration = 10,
+               max_bin = 32)
> model <- lgb.train(params,
+                  dtrain,
+                  2,
+                  valids,
+                  min_data = 1,
+                  learning_rate = 1,
```

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```

+               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 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 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
[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 depth=8

```

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```
[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 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.

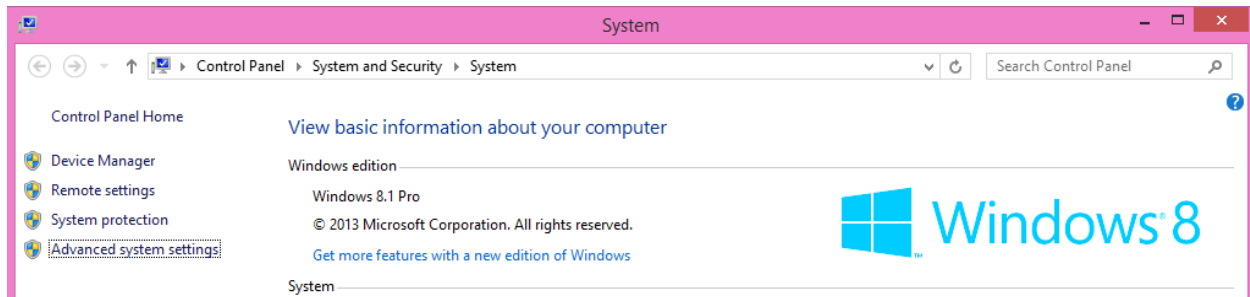
For this compilation tutorial, we are using AMD SDK for our OpenCL steps. However, you are free to use any OpenCL SDK you want, you just need to adjust the PATH correctly.

You will also need administrator rights. This will not work without them.

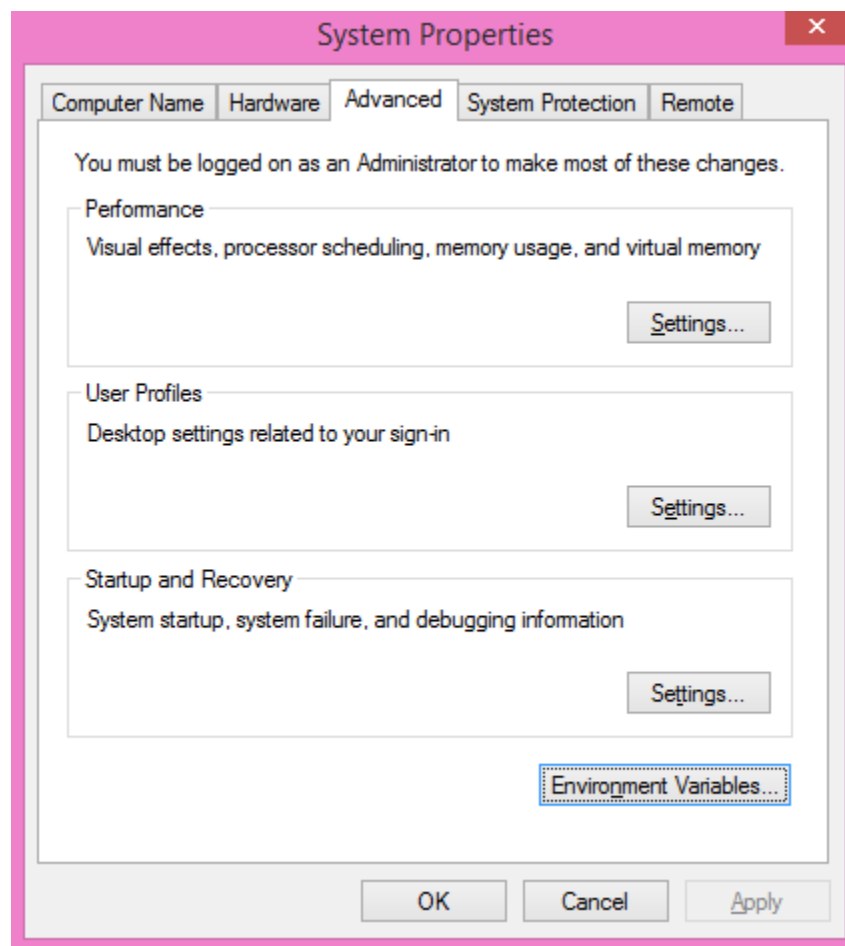
At the end, you can restore your original PATH.

17.1.1 Modifying PATH (for newbies)

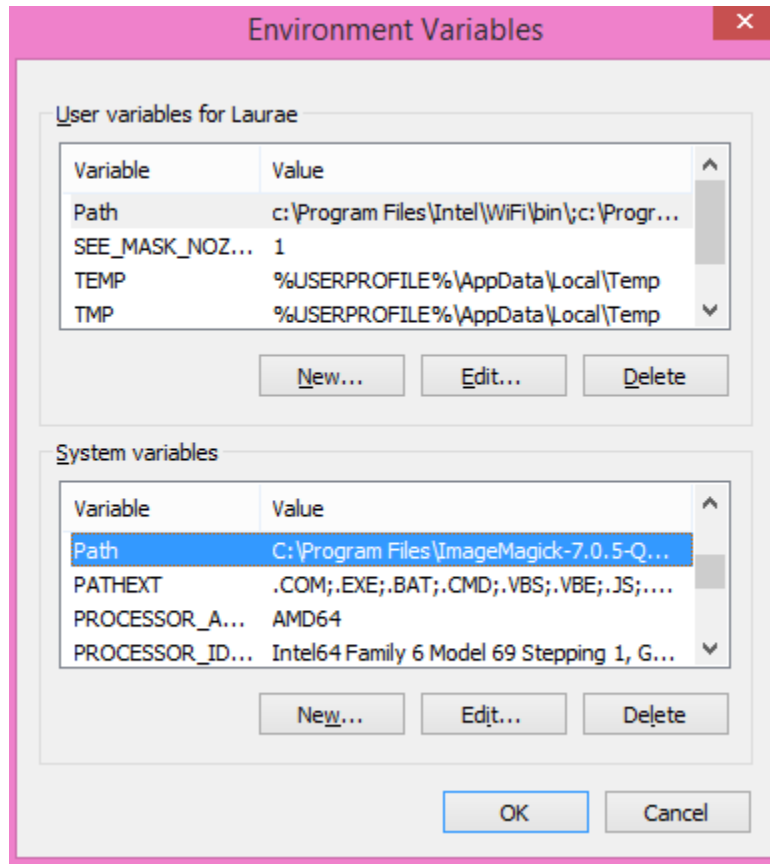
To modify PATH, just follow the pictures after going to the Control Panel:



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 (downloads for [Linux](#) and for [Windows](#)). You may want to replace the `OpenCL.dll` from the 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.

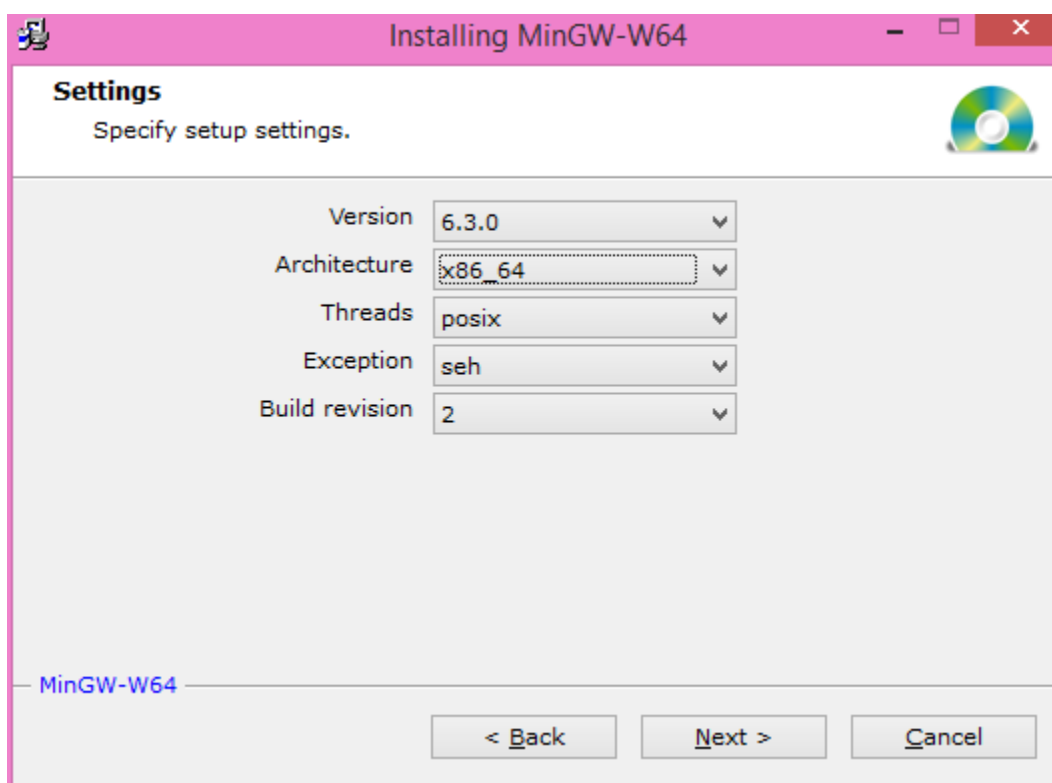
Further reading and correspondence table (especially if you intend to use cross-platform devices, like Intel CPU with AMD APP SDK): [GPU SDK Correspondence and Device Targeting Table](#).

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`:

```

Administrator: Command Prompt

C:\boost\boost_1_63_0\tools\build>gcc -v
Using built-in specs.
COLLECT_GCC=gcc
COLLECT_LTO_WRAPPER=c:/Rtools/mingw_32/bin/./libexec/gcc/i686-w64-mingw32/4.9.3/lto-wrapper.exe
Target: i686-w64-mingw32
Configured with: .././src/gcc-4.9.3/configure --host=i686-w64-mingw32 --build=i686-w64-mingw32 --target=i686-w64-mingw32 --prefix=/mingw32 --with-sysroot=/home/Jeroen/mingw-gcc-4.9.3/1686-493-posix-dwarf-rt-v3-s/mingw32 --with-gxx-include-dir=/mingw32/i686-w64-mingw32/include/c++ --enable-static --disable-shared --disable-multilib --enable-languages=c,c++,fortran,lto --enable-libstdcxx-time=yes --enable-threads=posix --enable-libgomp --enable-lto --enable-graphite --enable-checking=release --enable-fully-dynamic-string --enable-version-specific-runtime-libs --disable-sjlj-exceptions --with-dwarf2 --disable-lto --version-check --disable-clog-version-check --disable-libstdcxx-pch --enable-libstdcxx-debug --enable-bootstrap --disable-rpath --disable-win32-registry --disable-isl --enable-isl --disable-verror --disable-gyver --with-gnu-as --with-gnu-ld --with-arch=i686 --with-tune=generic --with-libiconv --with-system-zlib --with-mpc=/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-mpc=/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-clog=/home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static --enable-clog-backend=isl --with-pkgversion='1686-posix-dwarf, Built by MinGW-w64 project' --with-hugobolt-http://sourceforge.net/projects/mingw-w64/CFLAGS='-O2 -pipe -L/home/Jeroen/mingw-gcc-4.9.3/1686-493-posix-dwarf-rt-v3-s/mingw32/opt/include -L/home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static/include -L/home/Jeroen/mingw-gcc-4.9.3/1686-493-posix-dwarf-rt-v3-s/mingw32/opt/include -L/home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static/include -L/home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static/lib -L/home/Jeroen/mingw-gcc-4.9.3/prerequisites/i686-w64-mingw32-static/lib -Wl,-large-address-aware'
Thread model: posix
gcc version 4.9.3 (i686-posix-dwarf, Built by MinGW-w64 project)

C:\boost\boost_1_63_0\tools\build>

```

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.

NOTE: If you are using *Rtools* 4.0 or later, the path will have *mingw64* instead of *mingw_64* (PATH with *C:rtools40mingw64bin*), and *mingw32* instead of *mingw_32* (*C:rtools40mingw32bin*). The 32-bit version remains an unsupported solution under *Rtools* 4.0.

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-mgw53-mt-d-1_63.a
1 file(s) copied.
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\instantiate_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
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-mgw53-mt-d-1_63.a
common.copy C:\boost\boost-build\lib\libboost_wave-mgw53-mt-d-1_63.a
bin.v2\libs\wave\build\gcc-mingw-5.3.0\debug\link-static\threading-multi\libboost_wave-mgw53-mt-d-1_63.a
1 file(s) copied.
...updated 14621 targets...
C:\boost\boost_1_63_0>
```

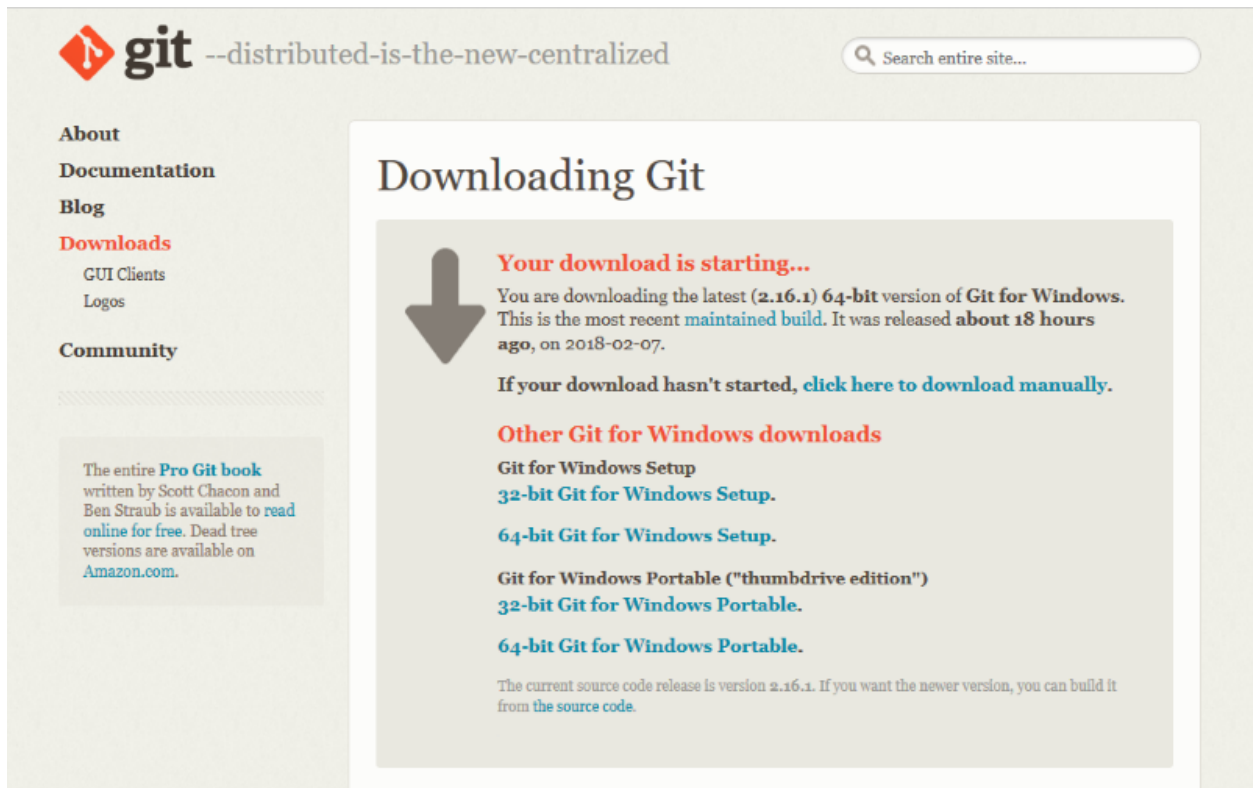
If you are getting an error:

- 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

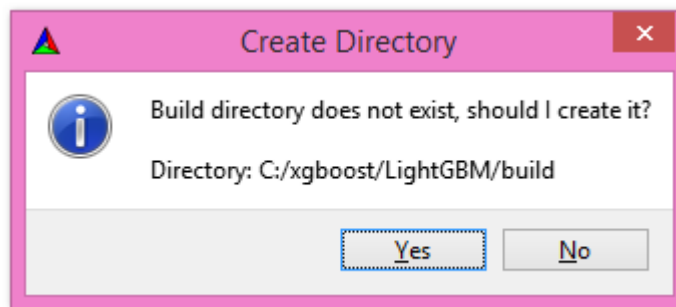
CLI / Python users only

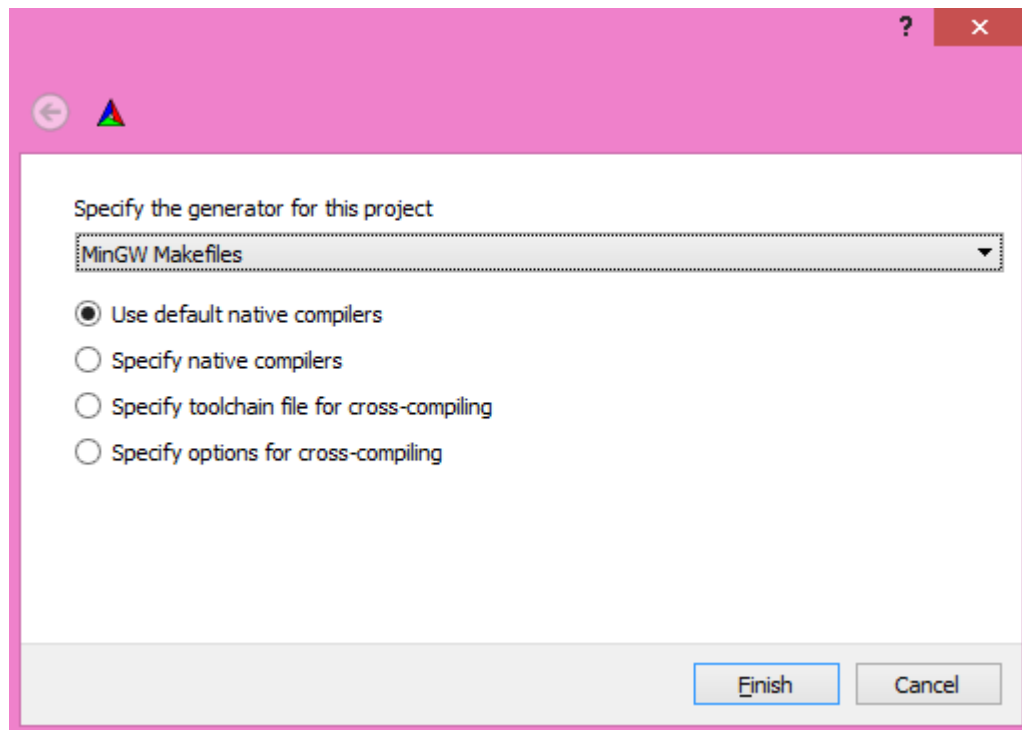
Installing CMake requires one download first and then a lot of configuration for LightGBM:

Binary distributions:

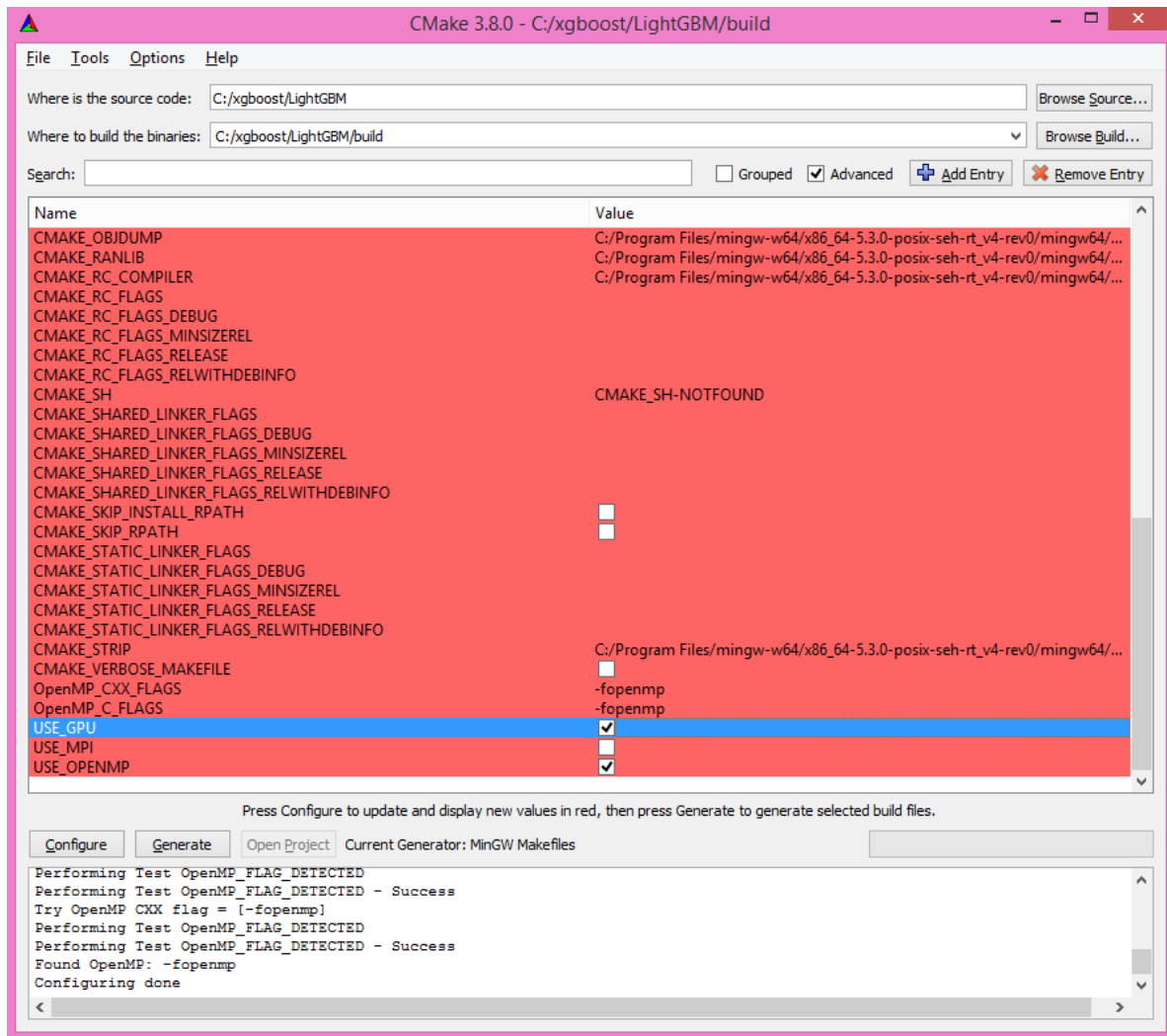
Platform	Files
Windows win64-x64 Installer: Installer tool has changed. Uninstall CMake 3.4 or lower first!	cmake-3.8.0-win64-x64.msi

- 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



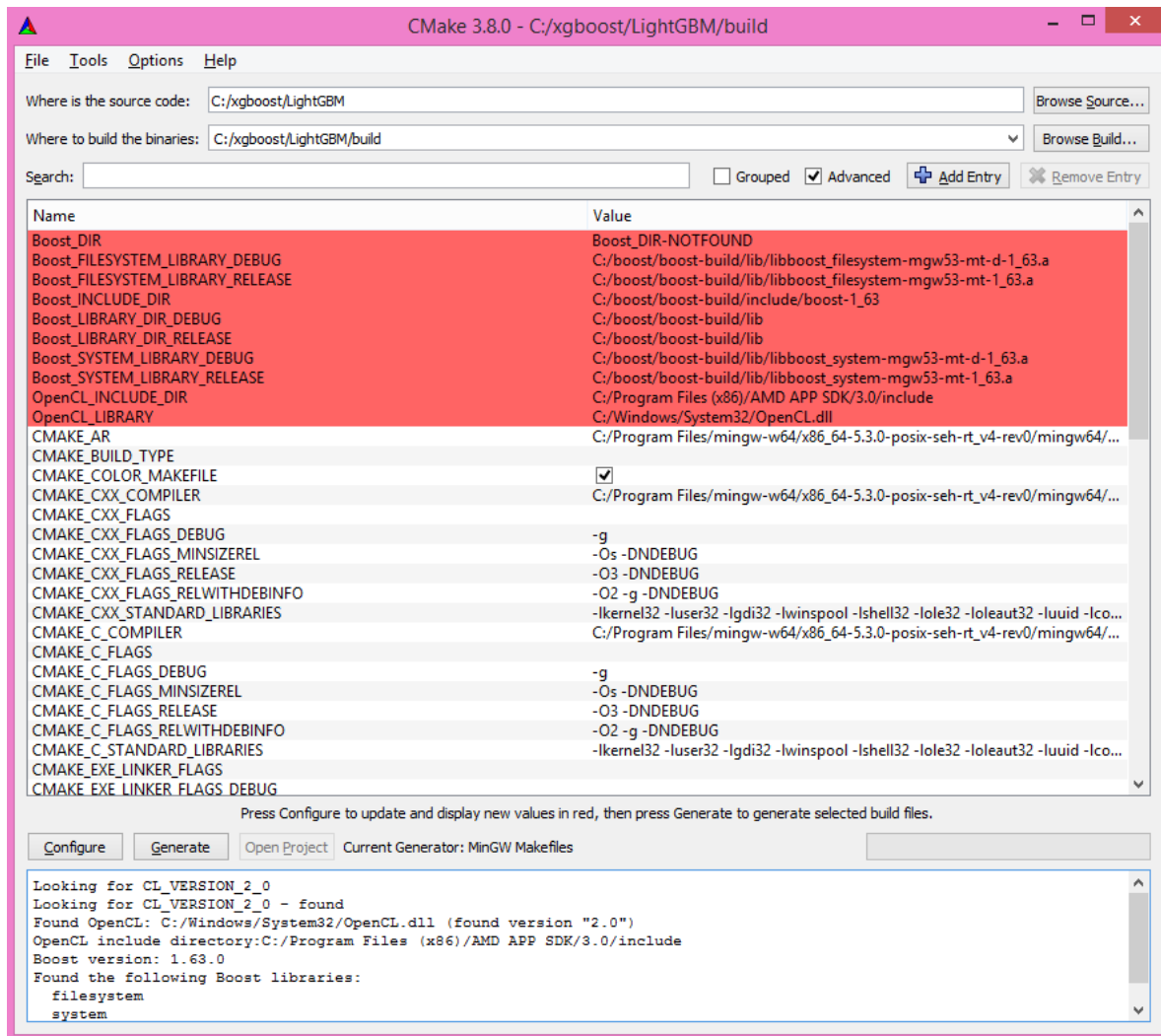


- Lookup for USE_GPU and check the checkbox



- 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,
h:8,
      from C:\xgboost\LightGBM\src\treelearner\parallel_tree_learner.
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
```

```

C:\xgboost\LightGBM\examples\binary_classification>../lightgbm.exe config=train.conf data=binary.train valid=binary.test objective=binary device=gpu
[LightGBM] [Info] Finished loading parameters
[LightGBM] [Info] Loading weights...
[LightGBM] [Info] Loading weights...
[LightGBM] [Info] Finished loading data in 0.081058 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 OpenCL 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 : 0.780862
[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 OpenCL Kernel with 256 bins...

Program received signal SIGSEGV, Segmentation fault.
0x00007ffbb37c11f1 in strlen (<) from C:\Windows\system32\msvcrt.dll
(gdb)

```

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.

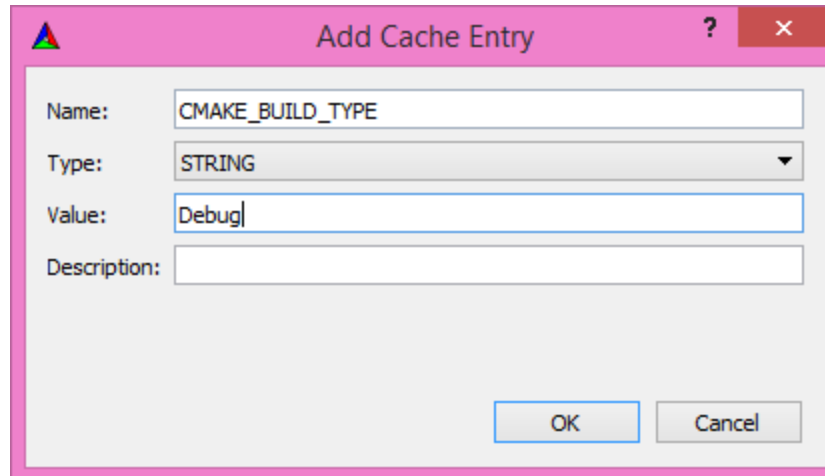
You will have to redo the compilation steps for LightGBM to add debugging mode. This involves:

- Deleting C:/github_repos/LightGBM/build folder
- Deleting lightgbm.exe, lib_lightgbm.dll, and lib_lightgbm.dll.a files

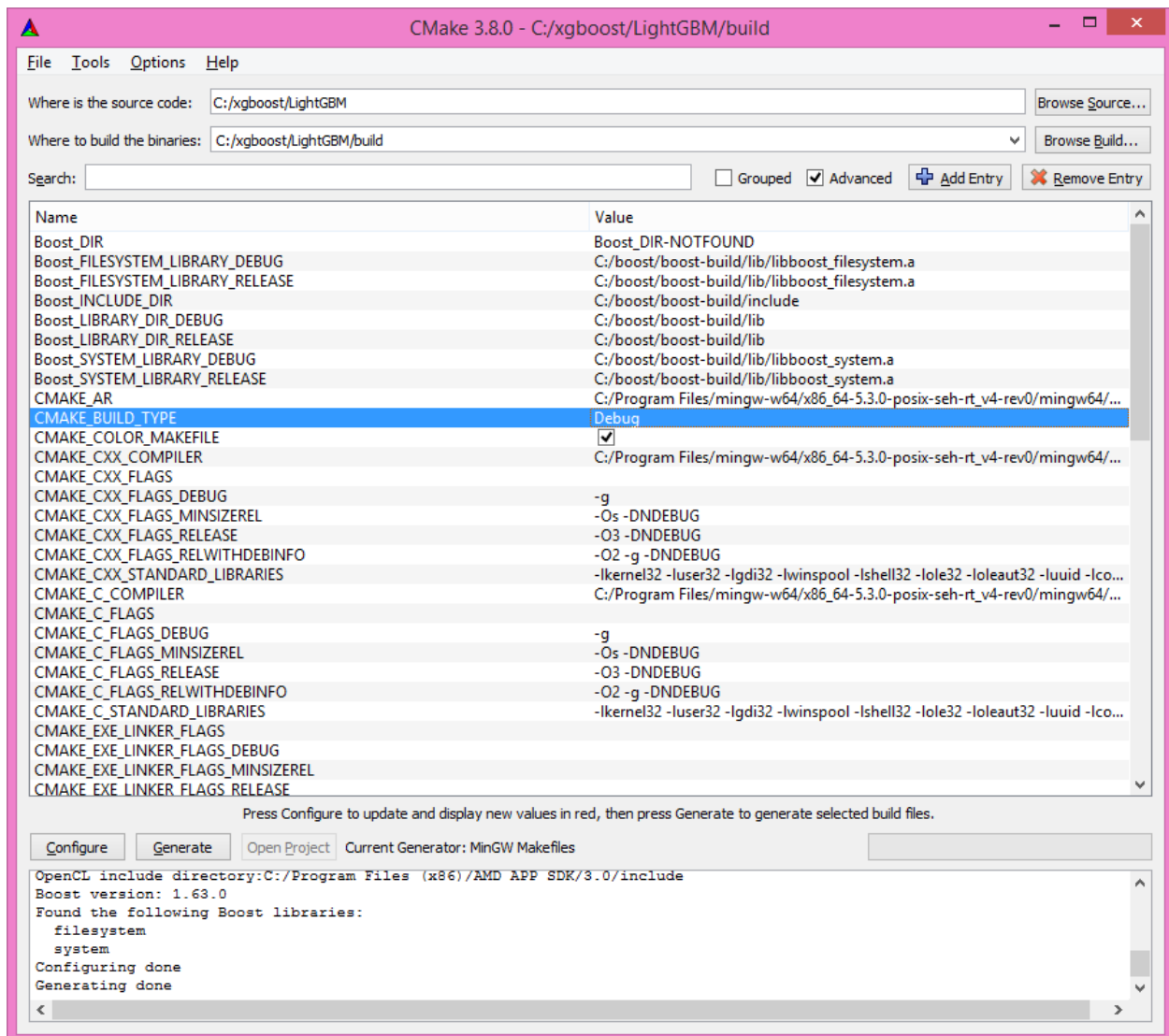
PC > Local Disk (C:) > xgboost > LightGBM

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”:



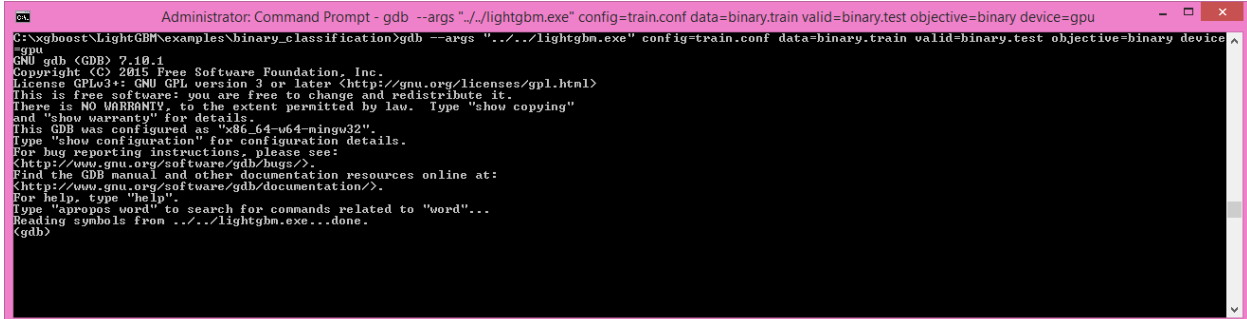
In addition, click on Configure and Generate:



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: 0land, 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  0x0000000000048bbe5 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  0x0000000000048eec3 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  0x000000000004913de in boost::compute::program::load_program_binary (hash=
↳"d27987d5bd61e2d28cd32b8d7a7916126354dc81", ctx=...)
    at C:/boost/boost-build/include/boost/compute/program.hpp:605
#6  0x00000000000490ece 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 (continues on next page)
```

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```

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::GPULearner::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::GPULearner::BuildGPUKernels_
↳(this=this@entry=0x3b9cac0)
  at C:\LightGBM\src\treelearner\gpu_tree_learner.cpp:569
#10 0x0000000000457b49 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 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---
#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

```

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```
[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

```
#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 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 0x0000000000454339 in LightGBM::GPULearner::BuildGPUKernels () at C:\LightGBM\
↳ src\trelearner\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
```

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```

#9  0x0000000000455e7e in LightGBM::GPULearner::BuildGPUKernels
↳ (this=this@entry=0x3b9cac0)
   at C:\LightGBM\src\treearner\gpu_tree_learner.cpp:569
#10 0x0000000000457b49 in LightGBM::GPULearner::InitGPU (this=0x3b9cac0, platform_id=
↳ <optimized out>, device_id=<optimized out>)
   at C:\LightGBM\src\treearner\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---
#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

```

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.

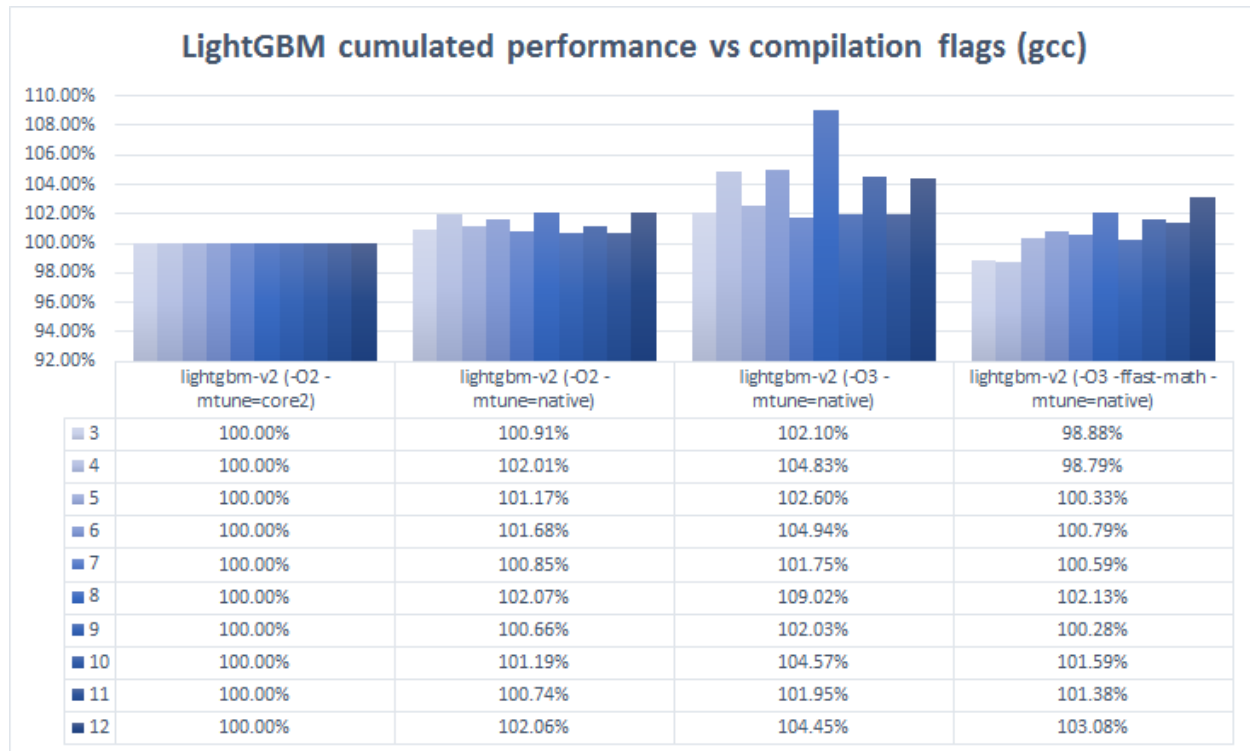
Using Intel Ivy Bridge CPU on 1M x 1K Bosch dataset, the performance increases as follow:

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](#)

The image below compares the runtime for training with different compiler options to a baseline using LightGBM compiled with `-O2 -mtune=core2`. All three options are faster than that baseline. The best performance was achieved with `-O3 -mtune=native`.



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
```


INDICES AND TABLES

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