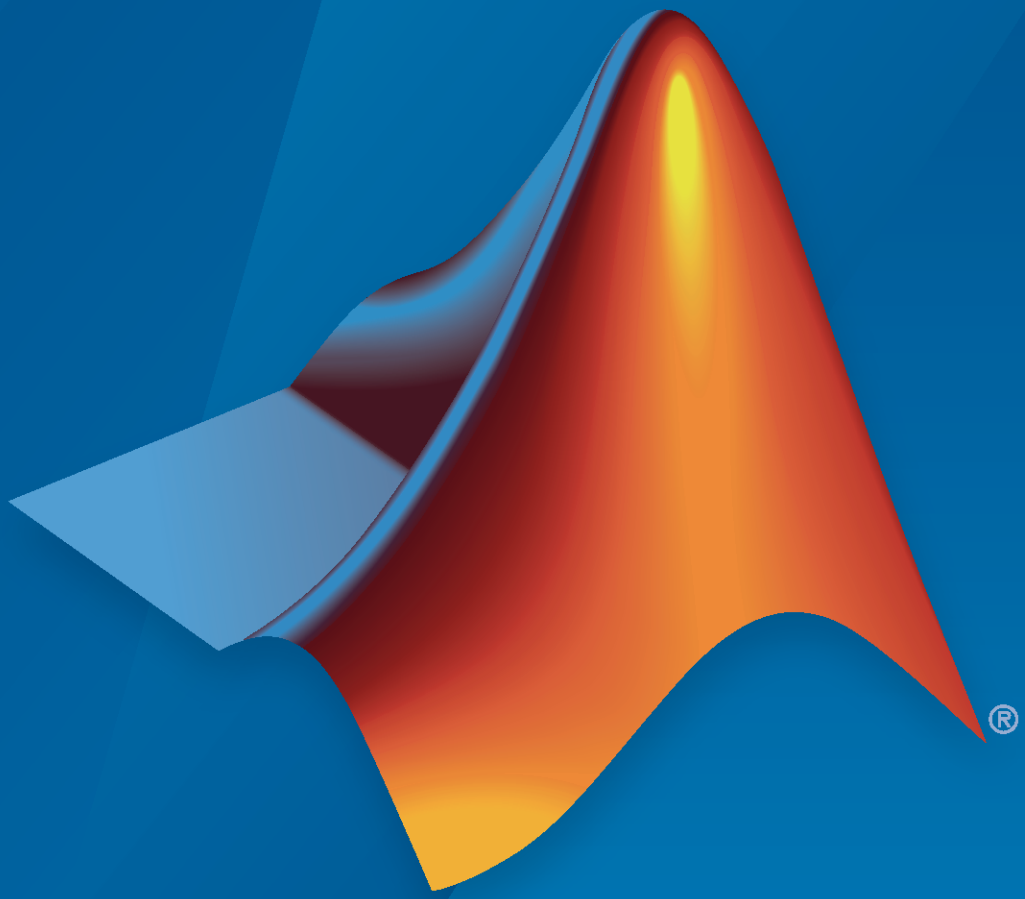
GPU Coder™ Release Notes



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GPU Coder™ Release Notes

Contents

R2023a

R2022b

R2022a

R2021a

R2020b

R2020a

R2019b

R2019a

R2018b

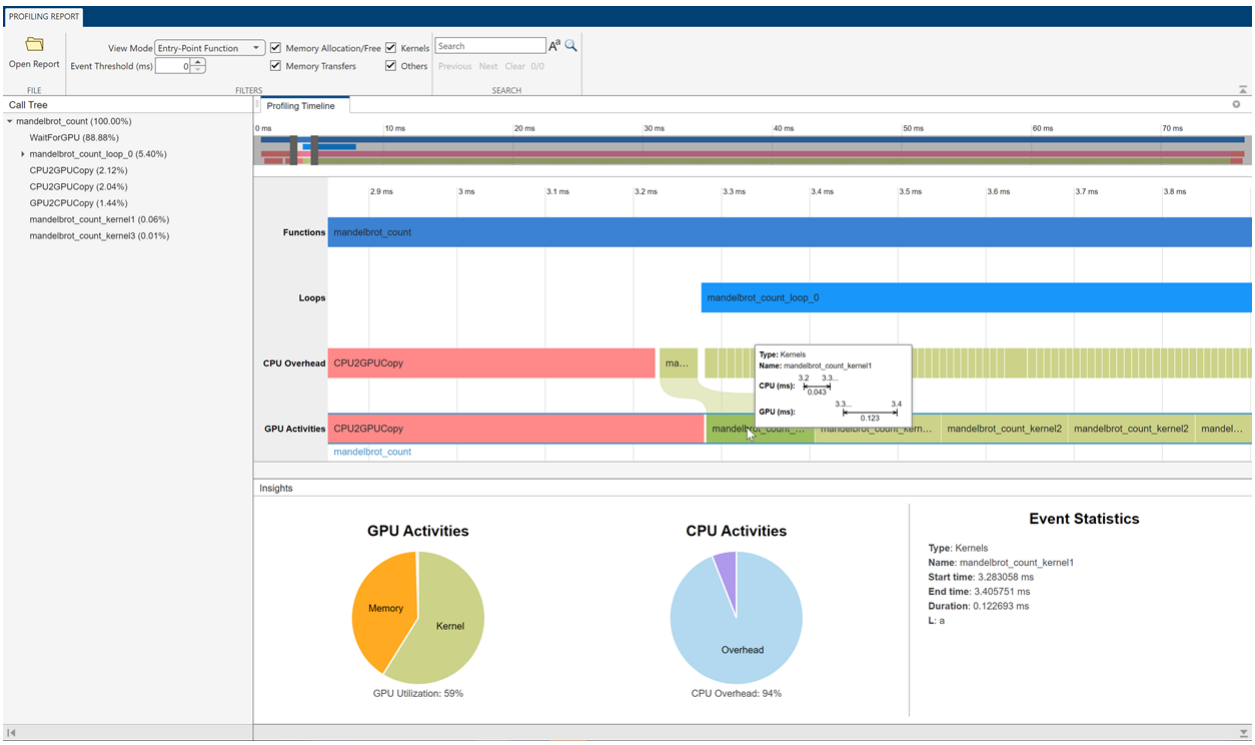
R2018a

R2017b

R2023a

Code Profiling: Use gpuPerformanceAnalyzer to visualize code metrics and identify optimization and tuning opportunities in your code

You can now use the `gpuPerformanceAnalyzer` function to analyze and optimize performance of the generated GPU code. The function opens the GPU Performance Analyzer window that exposes GPU and CPU activities, events, and performance metrics in a chronological timeline plot to accurately visualize, identify, and address performance bottlenecks in the generated CUDA® code.



For more information, see “GPU Performance Analyzer”.

For example, to analyze the performance of an addition algorithm, create an entry-point function in MATLAB® called `simpleAdd.m`.

```
function c = simpleAdd(a, b)

coder.gpu.kernelfun;
c = coder.nullcopy(zeros(size(a)));

for i = 1:numel(a)
    c(i) = a(i) + b(i);
end

end
```

To generate CUDA code for `simpleAdd.m` and analyze its performance, run this command in the MATLAB command window:

```
gpuPerformanceAnalyzer('simpleAdd',{ones(2048, 1),ones(2048, 1)});
```

For more information, see “Analyze Performance of the Generated CUDA Code”.

You can also use `gpuPerformanceAnalyzer` to profile deep learning applications and embedded applications that target NVIDIA® Jetson™ and NVIDIA DRIVE® platforms. To use `gpuPerformanceAnalyzer` for embedded targets, set the hardware property of the code configuration object to the appropriate target platform.

```
cfg = coder.gpuConfig('dll');
cfg.Hardware = coder.Hardware('NVIDIA Jetson');
gpuPerformanceAnalyzer('simpleAdd',{ones(2048, 1),ones(2048, 1)}, ...
Config = cfg);
```

For more information, see “Analyze Performance of Code Generated for Deep Learning Networks” and “GPU Profiling on NVIDIA Jetson Platforms” (MATLAB Coder Support Package for NVIDIA Jetson and NVIDIA DRIVE Platforms).

Compatibility Considerations

In previous releases, you use the `gpucoder.profile` function to create an execution profile report for generated CUDA code. Starting with R2023a, the `gpucoder.profile` function is no longer recommended. For more information, see “Compatibility Considerations”.

Stencil Processing: Additional capabilities and performance improvements for the stencilfun function

The R2023a release contains improvements to the `stencilfun` function that enable you to:

- Use variable-sized input arrays.
- Use `half` data type inputs.
- Use non-constant window size.

R2023a also includes memory optimizations that minimize data copies under certain conditions resulting in improved performance

Support for NVIDIA CUDA 11.8

GPU Coder™ now supports the use of CUDA toolkit version `11.8` for CUDA MEX or standalone code (static library, dynamically linked library, or executable program) generation.

For more information, see “Installing Prerequisite Products”.

Improved memory allocation for cell arrays, structures, and shared CPU-GPU variables

The R2023a release contains improvements to minimize memory copies when using cell arrays, structures, and variables accessed on both CPU and GPU. These improvements result in better run-time performance compared to previous releases.

Code generation for the pcfitcylinder function

In R2023a, you can generate optimized CUDA code for the `pcfitcylinder` from the Computer Vision Toolbox™.

Code generation for additional Lidar Toolbox function

You can now generate optimized CUDA code for the `extractFPFHFeatures` from the Lidar Toolbox™.

Generate code for variable-size dlarray data type

In R2023a, you can generate code for MATLAB code that uses variable-size `dlarray` objects.

For example, define this MATLAB design file:

```
function out = fooAdd(in1,in2) %#codegen
dlIn1_1 = dlarray(in1);
dlIn1_2 = dlarray(in2);
out = dlIn1_1 + dlIn1_2;
end
```

Specify the two inputs `in1` and `in2` to be unbounded two-dimensional arrays of `single` type. Create the appropriate code configuration object `cfg` to generate generic C MEX code for `fooAdd`. Generate MEX code and run the generated MEX.

```
t_in1 = coder.typeof(single(1),[inf inf],[1 1]);
t_in2 = coder.typeof(single(1),[inf inf],[1 1]);

codegen fooAdd -args {t_in1,t_in2} -report

out = fooAdd_mex(single(eye(4,4)),single(ones(4,1)));
```

When generating code for variable-size `dlarray` objects, adhere to these restrictions:

- The `U` dimension of a `dlarray` object must be of fixed size.
- If the `dlarray` data format `fmt` contains only one character, the corresponding data array `X` can have only one variable-size dimension. All other dimensions of `X` must be singleton.
- For operations between a `dlarray` object and a numeric array that might implicitly expand either operands, do not combine a fixed size `U` dimension of the `dlarray` object with a variable-size dimension of the numeric array.
- For unary operations such as `max`, `min`, and `mean` on a variable-size `dlarray` object, specify the intended working dimension explicitly as a constant value. See “Automatic dimension restriction”.

See “dlarray Limitations for Code Generation”.

Generate code for dlnetwork objects that accept variable sequence length inputs

In R2023a, you can generate code for `dlnetwork` objects that accept `dlarray` inputs with a variable-size time (T) dimension. You use such `dlarray` objects to represent time series data of variable sequence length.

For more information on how to create variable-size `dlarray` objects for code generation, see “Generate code for variable-size dlarray data type” on page 1-4.

Generate code that uses newer versions of NVIDIA cuDNN and TensorRT libraries

In R2023a, you can generate more efficient CUDA code for layers and networks that use these newer versions of NVIDIA CUDA deep neural network library (cuDNN) and NVIDIA TensorRT high performance inference libraries:

- NVIDIA CUDA deep neural network library (cuDNN), version 8.2.1.
- NVIDIA TensorRT 8.4.2.

For more information, see “Installing Prerequisite Products”.

R2022b

Use dynamically allocated C++ arrays in generated function interfaces

In most cases, when you generate code for a MATLAB function that accepts or returns an array, there is an array at the interface of the generated CUDA C++ function. For an array size that is unknown at compile time, or whose bound exceeds a predefined threshold, the memory for the generated array is dynamically allocated. In R2022b, the generated CUDA code can implement such dynamically allocated arrays by using a C++ class template named `coder::gpu_array`.

The `coder::gpu_array` template is defined in a header file named `coder_gpu_array.h` in the build folder. To use dynamically allocated arrays in your custom C++ code (for example, a custom main function) that you want to integrate with the generated code, include the `coder_gpu_array.h` and `coder_array.h` header files in your custom `.cu` files.

To change the default behavior of the code generator and produce `coder::gpu_array` data structures in the generated CUDA code, do one of the following:

- In a code configuration object (`coder.MexCodeConfig`, `coder.CodeConfig`, or `coder.EmbeddedCodeConfig`), set the `DynamicMemoryAllocationInterface` parameter to `'C++'`.
- In the GPU Coder app, on the **Memory** tab, set **Dynamic memory allocation interface** to `Use C++ coder::array`.

To learn how to use the `coder::gpu_array` template, see Use Dynamically Allocated C++ Arrays in Generated Function Interfaces.

Stencil Processing: Use stencilfun for additional capabilities and improved performance for stencil like operations on the GPU

R2022b introduces the `stencilfun` function to generate CUDA kernels for stencil like operations. Stencil kernel operations compute each element of the output array as a function of a small region of the input array. You can express many array and filtering operations as a stencil operation. Finite differences, convolution, median filtering, and finite-element methods are examples of operations that stencil processing can perform.

`[OUT_1, ..., OUT_N] = stencilfun(FUNC, X, W)` applies the function `FUNC` to each sliding window of size `W` of the input array `X`. `stencilfun` outputs a number of equally-sized output arrays equal to the number of outputs of `FUNC`. Each call made to `FUNC` computes a single element of each output array. The index of this element corresponds to the center of the sliding window in the input array. Optionally, you can use Name-value arguments and specify a padding value to apply to the elements of the input array. You can also apply a preprocessing function to all elements of the input array (including padding elements) before performing the stencil computation. For additional options and usage information, see `stencilfun`.

For example, to perform 2-D convolution of an array with a 5x5 filter by using the `stencilfun` function,

```
function Out = myconv(In, W)
fh = @(X) stencilFcn(X, W);
Out = stencilfun(fh, In, [5 5], Shape = 'same');
end
```

The stencil function `stencilFcn` is defined as:

```
function y = stencilFcn(X, W)
y = 0;
for j = 1:5
    for i = 1:5
        y = y + X(i,j) * W(i,j);
    end
end
end
```

For an additional example on stencil processing on the GPU, see Stencil Processing on GPU.

Compatibility Considerations

In previous releases, the `gpucoder.stencilKernel` created CUDA kernels for stencil operations on the GPU. Starting with R2022a, the `gpucoder.stencilKernel` function is no longer recommended. For more information, see Compatibility Considerations.

Deep Learning: Analyze and find issues in the network for code generation

Analyze code generation compatibility of a deep learning networks by using the `analyzeNetworkForCodegen` function. Use the network code generation analyzer to validate a `SeriesNetwork`, `DAGNetwork`, and `dlnetwork` for library targets such as `ARM Compute Mali`, `cuDNN`, `TensorRT` and detect problems before code generation. Problems that `analyzeNetworkForCodegen` detects include unsupported layers for code generation, network issues, built-in layer specific issues, and issues with custom layers.

The `analyzeNetworkForCodegen` function requires the MATLAB Coder™ Interface for Deep Learning and GPU Coder Interface for Deep Learning support packages. To download and install support package, use the Add-On Explorer. You can also download the support packages from MathWorks GPU Coder Team and MathWorks MATLAB Coder Team. For more information, see Analyze Network for Code Generation.

Generate code for dlnetwork objects that do not have input layers

In R2022b, you can generate code for `dlnetwork` (Deep Learning Toolbox) objects that do not contain input layers. This enables you to generate code for `dlnetwork` objects that do not represent entire models but are used as intermediate building blocks that you connect together to create complex networks. The generated code can take advantage of either the NVIDIA CUDA deep neural network library (cuDNN) or the NVIDIA TensorRT high performance inference library for NVIDIA GPUs.

Deep Learning Arrays: Generate code for more functions that use dlarray

In R2022b, you can generate code for additional MATLAB functions that use `dlarray` (Deep Learning Toolbox) inputs. You can now generate code for these functions:

- Size Manipulation functions — Use `repelem` to repeat copies of array elements.
- Size Manipulation functions — Use `repmat` to repeat copies of array.

- Error function — Use `erf` to compute the error function for each element of input.

To learn more about generating code from MATLAB functions when using `dlarray` (Deep Learning Toolbox), see Code Generation for dlarray.

Code generation for more Image Processing Toolbox functions

Generate optimized CUDA code for these additional Image Processing Toolbox™ functions:

- `adaptthresh` (Image Processing Toolbox)
- `histeq` (Image Processing Toolbox)
- `label2rgb` (Image Processing Toolbox)

New and updated examples

This release updates the following example:

- Deep Learning Prediction with NVIDIA TensorRT Library – This example has been updated to generate MEX files that perform 32-bit floating point, 8-bit integer and 16-bit floating point prediction.

This release adds the following new example:

- Code Generation for Object Detection Using YOLO v4 Deep Learning – This example shows how to generate standalone CUDA executable for a You Only Look Once v4 (YOLO v4) object detector. This example uses a lightweight version of the YOLO v4 network with fewer network layers. It uses a feature pyramid network as the neck and has two YOLO v4 detection heads. The network was trained on the COCO dataset.
- Code Generation For Aerial Lidar Semantic Segmentation Using PointNet++ Deep Learning – This example shows how to generate CUDA MEX code for a PointNet++ network for lidar semantic segmentation. This example uses a pretrained PointNet++ network that can segment unorganized lidar point clouds belonging to eight classes (buildings, cars, trucks, poles, power lines, fences, ground, and vegetation).
- Build a Map from Lidar Data using SLAM on GPU – Shows how to perform 3-D Lidar simultaneous localization and mapping (SLAM) on NVIDIA GPUs. This example uses 3-D lidar data from a vehicle mounted sensor to progressively build a map and estimate the trajectory of the vehicle by using the SLAM approach.

Functionality being removed or changed

Using the gpucoder.stencilKernel function to create kernels for stencil operations is not recommended
Still runs

`gpucoder.stencilKernel` is not recommended. Use `stencilfun` instead.

This table shows typical usages of `gpucoder.stencilKernel` and how to update your code to use `stencilfun` instead.

Not Recommended	Recommended

Convolution using `gpucoder.stencilKernel`:
 	
`function Out = myconv(In)`
`Out = gpucoder.stencilKernel(@stencilFcn, In, [5 5]);`
`end`
 	
`function y = stencilFcn(X)`
`W = rand(5);`
`y = 0;`
`for j = 1:5`
`  for i = 1:5`
`  y = y + X(i,j) * W(i,j);`
`  end`
`end`
`end`
	Convolution using `stencilfun`:
	
	`function Out = myconv(In)`
	`fh = @(X) stencilFcn(X);`
	`Out = stencilfun(fh, In, [5 5], Shape = 'same');`
	`end`
	
	`function y = stencilFcn(X)`
	`W = rand(5)`
	`y = 0;`
	`for j = 1:5`
	`  for i = 1:5`
	`  y = y + X(i,j) * W(i,j);`
	`  end`
	`end`
	`end`

Passing extra arguments to the stencil function.
 	
`weights = rand(5);`
`In = rand(100);`
`Out = gpucoder.stencilKernel(@stencilFcn, In, [5 5], 'same', weights);`
 	
`function y = stencilFcn(X, weights)`
`  y = 0;`
`  for i = 1 : 5`
`  for j = 1 : 5`
`  y = y + X(j,i) * weights(j,i);`
`  end`
`  end`
`end`
	Use anonymous function to pass extra arguments to the stencil function.
	
	`weights = rand(5);`
	`fh = @(X) stencilFcn(X, weights);`
	`In = rand(100);`
	`Out = stencilfun(fh, In, [5 5],Shape='same');`
	
	`function y = stencilFcn(X, weights)`
	`  y = 0;`
	`  for i = 1 : 5`
	`  for j = 1 : 5`
	`  y = y + X(j,i) * weights(j,i);`
	`  end`
	`  end`
	`end`

For more information, see `stencilfun`.

coder.getDeepLearningLayers function is not recommended
Still runs

`coder.getDeepLearningLayers` is not recommended. Use `analyzeNetworkForCodegen` instead.

For more information, see `analyzeNetworkForCodegen`.

Unified memory allocation mode on host being removed
Warns

In a future release, the unified memory allocation (`cudaMallocManaged`) mode will be removed when targeting NVIDIA GPU devices on the host development computer. You can continue to use unified memory allocation mode when targeting NVIDIA embedded platforms.

When generating CUDA code from MATLAB, set the `MallocMode` property of the `coder.gpuConfig` code configuration object to `'discrete'`.

When generating CUDA code from Simulink® models, select `'discrete'` for the **Memory mode** parameter in the **Code Generation** > **GPU Code** pane.

Code generation behavior change for dlarray inputs and outputs

Behavior change

In R2022b, the generated code creates structures for the `dlarray` inputs and outputs of entry-point functions. `Data` is a public field that you can directly access it.

In previous releases, the generated code uses class to represent the `dlarray` inputs and outputs of entry-point functions. In these releases, you use the initializing function `init` to access the `Data` field. This example shows the difference in the generated code between the two releases:

MATLAB Code	R2022a Generated Code	R2022b Generated Code

`% entry-point function`
`function out = foo(a)`
`    out = dims(a);`
`end`
 	
`% code generation`
`cfg = coder.config('dll');`
`cfg.TargetLang = 'C++';`
`codegen -config cfg  foo -args dlarray(ones(5,4), 'SC')`
	`// File: dlarray.h (generated)`
	`namespace coder {`
	`class FOO_DLL_EXPORT dlarray`
	`public:`
	`  void init(const double b_Data[`
	`  dlarray();`
	`  ~dlarray();`
	
	`private:`
	`  double Data[20];`
	`};`
	`}`
	
	`// File: main.cpp (generated)`
	`static void argInit_dlarray(coder::dlarray *result)`
	`{`
	`  double dv[20];`
	`  argInit_5x4_real_T(dv);`
	`  **result->init(dv);**`
	`}`
		`// File: foo_types.h (generated)`
		`namespace coder {`
		`struct dlarray {`
		`  double Data[20];`
		`  void init(double a[20]);`
		`}`
		`}`
		
		`// File: main.cpp (generated)`
		`static void argInit_dlarray(coder::dlar`
		`{`
		
		`  **argInit_5x4_real_T(result->Data);**`
		`}`

R2022a

Code Optimization: Minimize cudaMemcpy calls at function boundaries

Starting in R2022a, the code generator eliminates unnecessary `cudaMemcpy` calls in the generated CUDA code that might occur at the boundaries of functions that are not inlined.

For example, consider the MATLAB function `foo` that accepts a `double` array `in` as input, scales the input array, and returns an array of the same type and size as `in`.

```
function out = foo(in)
%#codegen

coder.gpu.kernelfun();
mid = in * 2;
out = foo1(mid);
end

function out = foo1(in)
coder.inline('never');
coder.gpu.kernelfun();
out = in + 3;
end
```

Generate a static CUDA library for the function `foo`, specifying the input as a 500-by-500 `double` type.

```
cfg = coder.gpuConfig('lib');

codegen -config cfg foo -args {ones(500,500)} -report
```

The generated code contains two kernels, `foo_kernel1` that scales the input array by 2 and `foo1_kernel2` that adds 3 to each element.

CUDA Kernels

Kernel Name	Thread Dimensions	Block Dimensions	Input Variables	Output Variables	Stream	Shared Memory Size	Minimum Blocks Per SM	Constant Memory	Parent Kernel
foo_kernel1	[512,1,1]	[489,1,1]	gpu_in,b_gpu_in		0	0	1	0	None
foo1_kernel2	[512,1,1]	[489,1,1]	in,gpu_out		0	0	1	0	None

In R2022a, the intermediate variable `mid` remains on the GPU, eliminating the `cudaMemcpys` that copy `mid` from `GPU>CPU>GPU` before calling the second kernel `foo1_kernel2`.

CUDA Memcpy (R2022a)

Destination Variable Name	Source Variable Name	Data Size	Direction	Conditional Variable	Stream
gpu_in	in	2000000	host->device	NO_ENCLOSING_CONDITION	0
out	gpu_out	2000000	device->host	NO_ENCLOSING_CONDITION	0

CUDA Memcpy (Previous Releases)

Destination Variable Name	Source Variable Name	Data Size	Direction	Conditional Variable	Stream
gpu_in	in	2000000	host->device	NO_ENCLOSING_CONDITION	0
	b_gpu_in	2000000	device->host	NO_ENCLOSING_CONDITION	0
gpu_in	in	2000000	host->device	NO_ENCLOSING_CONDITION	0
out	gpu_out	2000000	device->host	NO_ENCLOSING_CONDITION	0

GPU Memory Manager: Additional customization options for GPU memory pools

In R2022a, the GPU memory manager provides code configuration parameters listed in the table to manage allocation and deallocation of memory blocks within GPU memory pools.

Code Configuration Parameter	Description	Value
In a GPU code configuration object (`coder.gpuConfig`): `BlockAlignment` In the GPU Coder app: on the **GPU Code** tab, **Block Alignment**	Controls the alignment of the blocks. The block sizes (bytes) in the pool are a multiple of the specified value.	Positive integer that is a power of 2. Default value is 256.

Code Configuration Parameter	Description	Value
In a GPU code configuration object: `FreeMode` In the GPU Coder app: on the **GPU Code** tab, **Free Mode**	Controls when the memory manager frees the GPU device memory. When set to `'Never'`, the memory is freed only when the memory manager is destroyed. Use `'AtTerminate'` to free empty GPU pools when the `terminate` function is called in the generated code. For MEX targets, memory is freed after every call to the generated MEX function. For other targets, memory is freed when calling the terminate function. When set to `'AfterAllocate'`, empty pools are freed after each call to CUDA memory allocate.	`'Never'` (default) | `'AtTerminate'` | `'AfterAllocate'`
In a GPU code configuration object: `MinPoolSize` In the GPU Coder app: on the **GPU Code** tab, **Minimum Pool Size**	Specify the minimum pool size in megabytes (MB).	Positive integer that is a power of 2. Default value is 8.
In a GPU code configuration object: `MaxPoolSize` In the GPU Coder app: on the **GPU Code** tab, **Maximum Pool Size**	Specify the maximum pool size in megabytes (MB). The memory manager computes the size levels using the `MinPoolSize` and `MaxPoolSize` parameters by interpolating between the two values in increasing powers of 2. For example, if the `MinPoolSize` is 4 and the `MaxPoolSize` is 1024, the size levels are {4, 8, 16, 32, 64, 128, 256, 512, 1024}.	Positive integer that is a power of 2. Default value is 2048.

For more information, see GPU Memory Manager.

GPU Memory Manager: Use memory pools for CUDA libraries

Starting in R2022a, you can enable GPU Coder memory manager for efficient allocation and management of workspaces when generating code that uses NVIDIA CUDA libraries, such as cuFFT, cuBLAS, and cuSOLVER.

To use memory pools with CUDA libraries:

- In a GPU code configuration object (`coder.gpuConfig`), enable the `MemoryManager` and `EnableCUFFT`, `EnableCUBLAS`, or `EnableCUSOLVER` properties.
- In the GPU Coder app, on the **GPU Code** tab, select **GPU Memory Manager** and **Enable cuFFT**, **Enable cuBLAS**, or **Enable cuSOLVER**.
- In the Simulink Configuration Parameters dialog box, **Code Generation > GPU Code** pane, select the **Memory manager** and **cuFFT**, **cuBLAS**, or **cuSOLVER** parameters.

For more information, see GPU Memory Manager.

Simulink Code Generation: Control code generation using custom system target files

In R2022a, you can control the code generation stage of the build process by using custom system target files. For GPU code generation, any system target file compatible with C++ and based on `grt.tlc` or `ert.tlc` files is supported. For more information, see Code Generation from Simulink Models with GPU Coder.

To learn about creating custom target files, see Customize System Target Files (Simulink Coder).

Simulink Deep Learning: Generate code for dlnetwork workflows that use deep learning arrays

In R2022a, you can generate code for `dlnetwork` (Deep Learning Toolbox) and `dlarray` (Deep Learning Toolbox) that you use to run inference with `dlnetwork`. The `dlnetwork` object code generation supports the NVIDIA CUDA deep neural network library (cuDNN) and the NVIDIA TensorRT high performance inference library for NVIDIA GPUs.

You can use MATLAB Function block or the Predict or Image Classifier block from the **Deep Neural Networks** library to import the `dlnetwork` into Simulink.

Generate CUDA code for half-precision data types in MATLAB Function blocks

You can now generate CUDA code for half-precision data types in MATLAB Function blocks.

Code generation from MATLAB for dlnetwork objects that contain image sequences

Starting in R2022a, you can generate code for the `dlnetwork` (Deep Learning Toolbox) object that has image sequence inputs. Code generation support includes:

- A `dlarray` (Deep Learning Toolbox) input containing image sequences that have `'SSCT'` or `'SSCBT'` data formats.
- Multi-input `dlnetwork` with heterogeneous input layers.

For more information, see `dlnetwork` (Deep Learning Toolbox).

Deep Learning Arrays: Generate code for more functions that use dlarray

In R2022a, you can generate code for additional MATLAB functions that use `dlarray` (Deep Learning Toolbox) inputs. Code generation includes:

- Binary math operations — Use `power` to perform binary element-wise power (`.^`) operation.
- Other math operations — Perform matrix multiplication by using `mtimes`. Use `pagemtimes` to perform page-wise matrix multiplication.

Mixed-Precision Deep Learning: Perform inference in INT8 precision for fully connected layer

You can now generate code in 8-bit integer precision for the `fullyConnectedLayer` (Deep Learning Toolbox) by using the CUDA Deep Neural Network library (cuDNN) library.

Deep Learning Networks: Generate code for additional networks

Code generation by using the CUDA Deep Neural Network library (cuDNN) library supports these additional networks:

- `yolov4ObjectDetector` (Computer Vision Toolbox) – YOLO v4 object detector. This feature requires the functions in the Computer Vision Toolbox Model for YOLO v4 Object Detection support package.
- `yolov3ObjectDetector` (Computer Vision Toolbox) – YOLO v3 object detector. This feature requires the functions in the Computer Vision Toolbox Model for YOLO v3 Object Detection support package.
- `pointPillarsObjectDetector` (Lidar Toolbox) – PointPillars network to detect objects in lidar point clouds. This feature requires the Lidar Toolbox.

Code generation by using the NVIDIA TensorRT Library supports these additional networks:

- Convolutional plus recurrent neural networks.
- Stateful LSTM, BiLSTM, and GRU.
- `yolov4ObjectDetector` (Computer Vision Toolbox) – YOLO v4 object detector. This feature requires the functions in the Computer Vision Toolbox Model for YOLO v4 Object Detection support package.
- `yolov3ObjectDetector` (Computer Vision Toolbox) – YOLO v3 object detector. This feature requires the functions in the Computer Vision Toolbox Model for YOLO v3 Object Detection support package.
- `pointPillarsObjectDetector` (Lidar Toolbox) – PointPillars network to detect objects in lidar point clouds. This feature requires the Lidar Toolbox.

For more information, see Supported Networks, Layers, and Classes.

Deep Learning Layers: Generate code for additional layers

Code generation by using the CUDA Deep Neural Network library (cuDNN) supports these additional layers:

- `nnet.keras.layer.ClipLayer` (Deep Learning Toolbox™) clips the input between the upper and lower bounds.
- `nnet.keras.layer.PreluLayer` (Deep Learning Toolbox) for parametric rectified linear unit.
- `nnet.keras.layer.TimeDistributedFlattenCStyleLayer` (Deep Learning Toolbox) flattens a sequence of input image into a sequence of vector, assuming C-style (or row-major) storage ordering of the input layer.
- `nnet.onnx.layer.ClipLayer` (Deep Learning Toolbox) clips the input between the upper and lower bounds.
- `nnet.onnx.layer.GlobalAveragePooling2dLayer` (Deep Learning Toolbox) for global average pooling layer for spatial data.
- `nnet.onnx.layer.PreluLayer` (Deep Learning Toolbox) for parametric rectified linear unit.
- `nnet.onnx.layer.SigmoidLayer` (Deep Learning Toolbox) for sigmoid activation layer.
- `nnet.onnx.layer.TanhLayer` (Deep Learning Toolbox) for hyperbolic tangent activation layer.

Code generation by using the NVIDIA TensorRT Library supports these additional layers:

- `nnet.keras.layer.ClipLayer` (Deep Learning Toolbox) clips the input between the upper and lower bounds.
- `nnet.keras.layer.PreluLayer` (Deep Learning Toolbox) for parametric rectified linear unit.
- `nnet.keras.layer.TimeDistributedFlattenCStyleLayer` (Deep Learning Toolbox) flattens a sequence of input image into a sequence of vector, assuming C-style (or row-major) storage ordering of the input layer.
- `nnet.onnx.layer.ClipLayer` (Deep Learning Toolbox) clips the input between the upper and lower bounds.
- `nnet.onnx.layer.GlobalAveragePooling2dLayer` (Deep Learning Toolbox) for global average pooling layer for spatial data.
- `nnet.onnx.layer.PreluLayer` (Deep Learning Toolbox) for parametric rectified linear unit.
- `nnet.onnx.layer.SigmoidLayer` (Deep Learning Toolbox) for sigmoid activation layer.
- `nnet.onnx.layer.TanhLayer` (Deep Learning Toolbox) for hyperbolic tangent activation layer.

Code generation for ARM® Mali GPUs by using the ARM Compute Library supports these additional layers:

- `nnet.onnx.layer.GlobalAveragePooling2dLayer` (Deep Learning Toolbox) for global average pooling layer for spatial data.
- `nnet.onnx.layer.SigmoidLayer` (Deep Learning Toolbox) for sigmoid activation layer.
- `nnet.onnx.layer.TanhLayer` (Deep Learning Toolbox) for hyperbolic tangent activation layer.

For more information, see Supported Layers.

Code generation for more Image Processing Toolbox functions

Generate optimized CUDA code for these additional Image Processing Toolbox functions:

- `adapthisteq` (Image Processing Toolbox)
- `imfindcircles` (Image Processing Toolbox)
- `mat2gray` (Image Processing Toolbox)
- `regionfill` (Image Processing Toolbox)

Code generation for more Lidar Toolbox functions

Generate optimized CUDA code for these additional Lidar Toolbox functions:

- `pcfitcuboid` (Lidar Toolbox)
- `segmentGroundSMRF` (Lidar Toolbox)

Functionality being removed or changed

Unified memory allocation mode on host being removed

Warns

In a future release, the unified memory allocation (`cudaMallocManaged`) mode will be removed when targeting NVIDIA GPU devices on the host development computer. You can continue to use unified memory allocation mode when targeting NVIDIA embedded platforms.

When generating CUDA code from MATLAB, set the `MallocMode` property of the `coder.gpuConfig` code configuration object to `'discrete'`.

When generating CUDA code from Simulink models, select `'discrete'` for the **Memory mode** parameter in the **Code Generation > GPU Code** pane.

R2021b

GPU Memory Manager: Improve allocation efficiency and run-time performance through GPU memory pools

In R2021b, you can use the GPU memory manager for efficient memory allocation, management, and improving run-time performance. The GPU memory manager creates a collection of large GPU memory pools and manages allocation and deallocation of chunks of memory blocks within these pools. By creating large memory pools, the memory manager reduces the number of calls to the CUDA memory APIs, improving run-time performance. You can use the GPU memory manager for MEX and standalone CUDA code generation.

To enable the GPU memory manager, use one of these methods:

- In a GPU code configuration object (`coder.gpuConfig`), enable the `MemoryManager` property.
- In the GPU Coder app, on the **GPU Code** tab, select **GPU Memory Manager**.
- In the Simulink Configuration Parameters dialog box, **Code Generation > GPU Code** pane, select the **Memory manager** parameter.

Atomic Functions: Generate code that uses CUDA atomic intrinsics

In R2021b, you can generate code that takes advantage of CUDA device-wide arithmetic and bitwise atomic functions. Atomic functions perform read-modify-write operations on a value in the global or shared memory space of the GPU. These operations are performed atomically. No other thread can access this memory address before the read-modify-write operation is complete.

To generate the corresponding CUDA atomic function calls, use the GPU Coder function listed in this table.

Arithmetic Functions

Function Name	Description
`gpucoder.atomicAdd`	Atomically add a specified value to a variable in global or shared memory.
`gpucoder.atomicCAS`	Atomically compare and swap the value of a variable in global or shared memory.
`gpucoder.atomicDec`	Atomically decrement a variable in global or shared memory within a specified upper bound.
`gpucoder.atomicExch`	Atomically exchange a variable in global or shared memory with the specified value.
`gpucoder.atomicInc`	Atomically increment a variable in global or shared memory within a specified upper bound.
`gpucoder.atomicMax`	Atomically find the maximum value between a specified value and a variable in global or shared memory.
`gpucoder.atomicMin`	Atomically find the minimum value between a specified value and a variable in global or shared memory.
`gpucoder.atomicSub`	Atomically subtract a specified value from a variable in global or shared memory.

Bitwise Functions

Function Name	Description
`gpucoder.atomicAnd`	Atomically perform bitwise AND between a specified value and a variable in global or shared memory.
`gpucoder.atomicOr`	Atomically perform bitwise OR between a specified value and a variable in global or shared memory.
`gpucoder.atomicXor`	Atomically perform bitwise XOR between a specified value and a variable in global or shared memory.

Improvements to reduction operations by using gpucoder.reduce

The R2021b release contains improvements to the `gpucoder.reduce` function that enable you to:

- Perform reduction operations along a specified dimension.
- Apply a preprocessing function to the elements of the input array before performing the reduction operation.

For example, to find the `sum` and `max` of the elements of an array `A` along dimension 2, run this code:

```
function [s1,s2] = myReduce(A)
   [s1,s2] = gpucoder.reduce(A, {@mySum, @myMax},'dim',2);
end

function c = mySum(a,b)
   c = a+b;
end

function c = myMax(a,b)
   c = max(a,b);
end
```

To find the `sum` of the elements of an array `A` after scaling each element by 2, use this code:

```
function s = myReduce(A)
   s = gpucoder.reduce(A,@mySum,'preprocess',@myScale);
end

function c = mySum(a,b)
   c = a+b;
end

function b = myScale(a)
   b = 2*a;
end
```

Function Inlining: Fine-tune readability and speed of generated code

In R2021b, GPU Coder provides access to global inlining settings in the code configuration parameters that provides greater control over speed and readability of the generated MEX and standalone CUDA code.

In previous releases, GPU Coder always optimized inlining behavior for performance, ignoring these global settings in the code configuration parameters.

To control inlining, use these settings.

Code Configuration Parameter	Description	Options
In a code configuration object: `InlineBetweenUserFunctions` In the GPU Coder app: On the **All Settings** tab, **Inline between user functions**	Controls inlining behavior at all call sites where a function that you wrote calls another function that you wrote	`'Always'` (default) | `'Speed'` | `'Readability'` | `'Never'`
In a code configuration object: `InlineBetweenMathWorksFunctions` In the GPU Coder app: On the **All Settings** tab, **Inline between MathWorks functions**	Controls inlining behavior at all call sites where a MathWorks® function calls another MathWorks function	`'Always'` (default) | `'Speed'` | `'Readability'` | `'Never'`
In a code configuration object: `InlineBetweenUserAndMathWorksFunctions` In the GPU Coder app: On the **All Settings** tab, **Inline between user and MathWorks functions**	Controls inlining behavior at all call sites where a function that you wrote calls a MathWorks function, or a MathWorks function calls a function that you wrote	`'Always'` (default) | `'Speed'` | `'Readability'` | `'Never'`

Option descriptions:

- `'Always'`: Always performs inlining at a call site.
- `'Speed'`: Uses internal heuristics to determine whether to perform inlining at a call site. This setting usually leads to highly optimized code.
- `'Readability'`: Almost never inlines function calls, except for calls to very small functions. Preserves modularity of code without sacrificing too much speed, whenever possible. Results in highly readable code.
- `'Never'`: Never inlines function calls. Results in maximum readability. This setting might significantly reduce the performance of the generated code.

For more information, see Control Inlining to Fine-Tune Performance and Readability of Generated Code.

GPU Profiling: Generate code execution profiling report by using NVIDIA Nsight Systems

You can now use `gpucoder.profile` with the NVIDIA Nsight systems software to generate an execution profiling report for the generated CUDA code. The report provides metrics that help you analyze your application algorithms and identify opportunities to optimize performance.

For version and setup requirements of NVIDIA Nsight systems, see Installing Prerequisite Products and Setting Up the Prerequisite Products.

To learn about execution profiling by using the `gpucoder.profile` function, see GPU Execution Profiling of the Generated Code.

Deep Learning Workflow: Update network parameters after code generation

In R2021b, you can update learnable and state parameters of deep learning networks without regenerating code for the network. You can update the network parameters for `SeriesNetwork`, `DAGNetwork` and `dlnetwork`. Use the `coder.regenerateDeepLearningParameters` function to regenerate files containing network learnables and states parameters. Parameter update supports MEX and standalone code generation for the NVIDIA CUDA deep neural network library (cuDNN) and the NVIDIA TensorRT high performance inference libraries.

For more information, see Update Network Parameters After Code Generation. For an example on how to incrementally update the network learnables of a deep learning network, see Post-Code-Generation Update of Deep Learning Network Parameters.

Deep Learning Arrays: Generate code for more functions that use dlarray

In R2021b, you can generate code for additional MATLAB functions that use `dlarray` (Deep Learning Toolbox) inputs. Code generation support includes:

- Unary math operations — Find the inverse tangent by using `atan2`.
- Binary math operations — Use `minus`(`-`), `plus`(`+`), `rdivide`(`./`), and `times`(`.*`) to perform binary element-wise math operations.
- Reduction operations — Perform reduction operations on `dlarray` by using `mean`, `prod`, and `sum`.
- Comparison operations — Use `max` and `min` to find the maximum or minimum elements of a single `dlarray` or between two formatted `dlarray` inputs.
- Indexing operations — Use `colon`, `:` for indexing into a `dlarray`.
- Logical operations — Use functions such as `and` and `eq` to perform logical operations on the data within `dlarray`. For other supported logical operations, see Logical Operations.
- Size manipulation functions — Manipulate the dimensions of a `dlarray` by using `reshape` and `squeeze`.
- Transposition operations — Use `ctranspose`, `permute`, `ipermute`, and `transpose` to transpose `dlarray` matrices.
- Concatenation functions — Concatenate deep learning arrays by using `cat`, `horzcat`, and `vertcat`.
- Conversion functions — Change the underlying `dlarray` data type by using the `cast` function.
- Size identification functions — Query the dimensions of the `dlarray` data by using `iscolumn`, `ismatrix`, `isrow`, `isscalar`, and `isvector`.

Custom Layers: Use dlarray in deep learning networks that have custom layers

You can now generate code for custom deep learning layers that use deep learning arrays. Custom layer code generation supports unformatted and formatted `dlarray` (Deep Learning Toolbox) for MEX and standalone workflows. For other usage notes and limitations of custom layers with `dlarray`, see Custom Layers.

Code generation from MATLAB for dlnetwork that contains sequences

In R2021b, you can generate code for `dlnetwork` (Deep Learning Toolbox) that has vector sequence inputs. Code generation support includes:

- `dlarray` (Deep Learning Toolbox) containing vector sequences that have `'CT'` or `'CBT'` data formats.
- A `dlnetwork` object that has multiple inputs.

For more information, see `dlnetwork` (Deep Learning Toolbox).

Mixed-Precision Deep Learning: Perform inference in INT8 precision for additional networks

Code generation by using the NVIDIA TensorRT Library with inference computation in 8-bit integer precision supports these additional networks:

- Object detector networks such as YOLOv2 and SSD.
- Regression and semantic segmentation networks.

For more information, see Deep Learning Prediction by Using NVIDIA TensorRT.

Simulink Deep Learning: Generate code for custom layers

In R2021b, you can generate CUDA code from Simulink models that have deep learning networks containing custom layers. Custom layer code generation supports the NVIDIA CUDA deep neural network library (cuDNN) and the NVIDIA TensorRT high performance inference library for NVIDIA GPUs. When targeting the cuDNN library, the code generator supports both row-major and column-major code generation for custom layers.

For other usage notes and limitations, see Custom Layers.

Deep Learning Layers: Generate code for additional layers

Code generation by using the CUDA Deep Neural Network library (cuDNN) supports this additional layer:

- `groupNormalizationLayer` (Deep Learning Toolbox) normalizes a mini-batch of data across grouped subsets of channels for each observation independently.

Code generation by using the NVIDIA TensorRT Library supports this additional layer:

- `groupNormalizationLayer` (Deep Learning Toolbox) normalizes a mini-batch of data across grouped subsets of channels for each observation independently.

For more information, see Supported Layers.

Code generation for page-wise matrix multiplication

In R2021b, you can generate CUDA code for the `pagemtimes` function to perform batched matrix multiplication on pages of N-D arrays.

For usage notes and limitations, see `pagemtimes`.

Code generation for additional Computer Vision Toolbox functions

In R2021b, you can generate optimized CUDA code for these additional Computer Vision Toolbox toolbox functions:

- `pcdenoise` (Computer Vision Toolbox)
- `pcmerge` (Computer Vision Toolbox)
- `pcnormals` (Computer Vision Toolbox)
- `pctransform` (Computer Vision Toolbox)
- `pcfitplane` (Computer Vision Toolbox)
- `pcmapndt` (Computer Vision Toolbox)

Code generation for more Image Processing Toolbox functions

Generate optimized CUDA code for these additional Image Processing Toolbox toolbox functions:

- `regionprops` (Image Processing Toolbox)
- `imbilatfilt` (Image Processing Toolbox)

Code generation for additional Signal Processing Toolbox function

- `resample` (Signal Processing Toolbox)

New and updated examples

This release updates the following example:

- Code Generation for a Deep Learning Simulink Model that Performs Lane and Vehicle Detection – This example has been updated to use the new Deep Learning Object Detector (Computer Vision Toolbox) block from the Computer Vision Toolbox.

This release adds the following new example:

- Ground Plane Segmentation and Obstacle Detection on NVIDIA Jetson Xavier™ NX Embedded platform – This example shows ground plane segmentation of 3-D lidar data from a vehicle on NVIDIA embedded platforms to find nearby obstacles. The example uses ground plane segmentation and obstacle detection application to illustrate:

    - C++ and CUDA code generation for the ground plane segmentation and obstacle detection algorithm by using MATLAB Coder and GPU Coder.
    - Verify behavior of the generated code on the target platform by using processor-in-the-loop (PIL) simulation.
    - Compare of the performance of the application on the CPU (C++) and the GPU (CUDA).
- Quantize Residual Network Trained for Image Classification and Generate CUDA Code – This example shows how to quantize the learnable parameters in the convolution layers of a deep learning neural network that has residual connections and has been trained for image classification with CIFAR-10 data.
- Quantize Object Detectors and Generate CUDA® Code – This example shows how to generate CUDA code for an SSD vehicle detector and a YOLO v2 vehicle detector that performs inference computations in 8-bit integers.
- Parameter Pruning and Quantization of Image Classification Network – This example shows how to prune the parameters of a trained neural network using two parameter score metrics: The magnitude score and Synaptic Flow score.
- Generate CUDA ROS Node from Simulink (ROS Toolbox) – This example shows you how to generate and build a CUDA ROS node from a Simulink model.
- Lane and Vehicle Detection in ROS Using YOLO v2 Deep Learning Algorithm (ROS Toolbox) – This example shows how to use deep convolutional neural networks inside a ROS enabled Simulink model to perform lane and vehicle detection. In this example, you first read traffic video as input and publish them as sensor or image messages to a topic on the ROS network. Then you detect vehicles, the left and right lane boundaries corresponding to the ego vehicle in every frame, annotate the input image with the detections and publish them to a topic in the ROS network. Finally, you generate CUDA optimized code for the ROS node from the Simulink model for lane and vehicle detection.
- Sign Following Robot Using YOLOv2 Detection Algorithm with ROS in Simulink (ROS Toolbox) – This example shows how to use Simulink to control a simulated robot running on a separate ROS-based simulator. It then shows how to generate CUDA-optimized code for the ROS node, from the Simulink model and deploy it to the localhost device.

To see the full list of examples for GPU Coder, at the MATLAB command line, enter `doc gpucoder`.

Functionality being removed or changed

cnncodegen Function: ARM Mali target support only

In R2021b, the `cnncodegen` function generates C++ code for only the ARM Mali GPU processor by using the ARM Compute Library for computer vision and machine learning.

For all other targets, use the `codegen` command. To learn about targeting cuDNN targets by using the `codegen` function, see Code Generation for Deep Learning Networks by Using cuDNN. To learn about targeting TensorRT targets by using the `codegen` function, see Code Generation for Deep Learning Networks by Using TensorRT.

Unified memory allocation mode on host being removed

Warns

In a future release, the unified memory allocation (`cudaMallocManaged`) mode will be removed when targeting NVIDIA GPU devices on the host development computer. You can continue to use unified memory allocation mode when targeting NVIDIA embedded platforms.

When generating CUDA code from MATLAB, set the `MallocMode` property of the `coder.gpuConfig` code configuration object to `'discrete'`.

When generating CUDA code from Simulink models, select `'discrete'` for the **Memory mode** parameter in the **Code Generation > GPU Code** pane.

R2021a

Code Optimization: Control the number of blocks created during kernel launch

In R2021a, you can specify the maximum number of blocks created during a kernel launch. Because GPU devices have limited streaming multiprocessor (SM) resources, limiting the number of blocks for each kernel can avoid performance losses from scheduling, loading and unloading of blocks. To specify the maximum number of blocks for each kernel, use one of these methods:

- In a GPU code configuration object (`coder.GpuCodeConfig`), set a valid value for the `MaximumBlocksPerKernel` property.
- In the GPU Coder app, on the **GPU Code** tab, set a valid value for **Maximum Blocks Per Kernel**.
- In the Simulink Configuration Parameters dialog box, **Code Generation > GPU Code** pane, set a valid value for the **Maximum blocks per kernel** parameter.

If the number of iterations in a loop is greater than the maximum number of blocks per kernel, the code generator creates CUDA kernels with striding.

When you specify the maximum number of blocks for each kernel, the code generator creates 1-D kernels. To force the code generator to create 2-D or 3-D kernels, use the `coder.gpu.kernel` pragma. The `coder.gpu.kernel` pragma takes precedence over the maximum number of kernels for each block.

Generate code from MATLAB for dlnetwork workflows that uses deep learning arrays

In R2021a, you can generate code for `dlnetwork` (Deep Learning Toolbox) and `dlarray` (Deep Learning Toolbox) that you use to run inference with `dlnetwork`. Code generation support includes:

- Construction of formatted and unformatted `dlarray`
- Passing `dlarray` to entry-point functions and returning `dlarray` from entry-point functions
- Invoking a subset of functions on `dlarray` objects, including the object functions `softmax` (Deep Learning Toolbox), `sigmoid` (Deep Learning Toolbox), and `fullyconnect` (Deep Learning Toolbox)
- Passing formatted `dlarray` to the `dlnetwork` predict function inside an entry-point function.

See:

- Help topic: Code Generation for dlarray
- Example: Generate Digit Images on NVIDIA GPU Using Variational Autoencoder

Generate code that uses newer versions of NVIDIA cuDNN and TensorRT libraries

In R2021a, you can generate CUDA code for layers and networks that uses these newer versions of NVIDIA CUDA deep neural network library (cuDNN) and TensorRT high performance inference library for NVIDIA GPUs.

- NVIDIA CUDA deep neural network library (cuDNN), version 8.1.0.
- NVIDIA TensorRT high performance inference library, version 7.2.x.

See Installing Prerequisite Products.

Compatibility Considerations

When performing inference in `INT8` (8-bit integer) precision using cuDNN version 8.1.0, issues in the NVIDIA library may cause significant degradation in performance.

Deep Learning Layers: Generate code for additional layers

Code generation by using the CUDA Deep Neural Network library (cuDNN) supports this additional layer:

- `featureInputLayer` (Deep Learning Toolbox) inputs feature data to a network and applies data normalization.

Code generation by using the cuDNN library with inference computation in 8-bit integer precision supports this additional layer:

- `maxPooling2dLayer` (Deep Learning Toolbox) performs down-sampling by dividing the input into rectangular pooling regions and computing the maximum of each region.

Code generation by using the NVIDIA TensorRT Library supports this additional layer:

- `featureInputLayer` (Deep Learning Toolbox) inputs feature data to a network and applies data normalization.

Code generation for ARM Mali GPUs using the ARM Compute Library supports this additional layer:

- `featureInputLayer` (Deep Learning Toolbox) inputs feature data to a network and applies data normalization.

For more information, see Supported Networks and Layers.

Code generation for additional Computer Vision Toolbox functions

In R2021a, you can generate optimized CUDA code for these additional Computer Vision Toolbox toolbox functions:

- `pcregisterndt` (Computer Vision Toolbox)
- `pcdownsample` (Computer Vision Toolbox)
- `pcbin` (Computer Vision Toolbox)
- `segmentGroundFromLidarData` (Computer Vision Toolbox)

Code generation for additional Wavelet Toolbox functions

In R2021a, you can generate optimized CUDA code for these additional Wavelet Toolbox™ toolbox functions:

- **Discrete Wavelet Transforms** — `waverec` (Wavelet Toolbox) and `waverec2` (Wavelet Toolbox)
- **Denoising** — `wdenoise` (Wavelet Toolbox) and `wdenoise2` (Wavelet Toolbox)

Code generation for additional MATLAB functions

In R2021a, you can generate optimized CUDA code for these additional MATLAB toolbox functions:

- `histcounts`
- `interp1`

GPU Coder Support Package for NVIDIA GPUs is moved to MATLAB Coder Support Package for NVIDIA Jetson and NVIDIA DRIVE Platforms

Starting in R2021a, the GPU Coder Support Package for NVIDIA GPUs is named MATLAB Coder Support Package for NVIDIA Jetson and NVIDIA DRIVE Platforms. To use this support package in R2021a, you must have the MATLAB Coder product. For more information, see GPU Coder Supported Hardware.

Functionality being removed or changed

cnncodegen Function: ARM Mali target support only
Warns

In a future release, the `cnncodegen` function will generate C++ code and build a static library for only the ARM Mali GPU processor. You can continue to use the `'arm-compute-mali'` value for the `'targetlib'` argument to target an ARM Mali GPU by using the ARM Compute Library for computer vision and machine learning.

For all other targets, use the `codegen` command. To learn about targeting cuDNN targets by using the `codegen` function, see Code Generation for Deep Learning Networks by Using cuDNN. To learn about targeting TensorRT targets by using the `codegen` function, see Code Generation for Deep Learning Networks by Using TensorRT.

Deprecating support for unified memory allocation mode on host
Behavior change in future release

In a future release, support for the unified memory allocation (`cudaMallocManaged`) mode will be removed when targeting NVIDIA GPU devices on the host development computer. You can continue to use unified memory allocation mode when targeting NVIDIA embedded platforms.

When generating CUDA code from MATLAB, set the `MallocMode` property of the `coder.gpuConfig` code configuration object to `'discrete'`.

When generating CUDA code from Simulink models, select `'discrete'` for the **Memory mode** parameter in the **Code Generation>GPU Code** pane.

R2020b

Simulink Support: Generate, build, and deploy Simulink models to NVIDIA GPUs

In R2020b, you can use GPU Coder to generate and execute optimized CUDA C++ code from Simulink models that contain MATLAB Function blocks. The generated code calls optimized NVIDIA CUDA libraries, including cuFFT, cuSolver, and cuBLAS.

You can use the generated CUDA code within Simulink to:

- Speed up the execution of your Simulink model by using NVIDIA GPUs. When you simulate a model that contains a MATLAB Function block, the software generates CUDA MATLAB executable (MEX) code from the block and dynamically links the generated code to Simulink. For more information, see Simulation Acceleration by Using GPU Coder.
- Build an executable that you can use for rapid prototyping on NVIDIA GPUs. For more information, see Code Generation from Simulink Models by Using GPU Coder.
- Deploy the Simulink models on embedded NVIDIA GPUs such as Jetson and DRIVE by using the MATLAB Coder Support Package for NVIDIA Jetson and NVIDIA DRIVE Platforms. You can also remotely communicate with the NVIDIA target and control the peripheral devices for prototyping. For more information, see Targeting NVIDIA Embedded Boards.

Deep Learning Simulink Support: Generate, build, and deploy deep learning networks in Simulink models to NVIDIA GPUs

In this release, you can use GPU Coder to generate and execute optimized CUDA C++ code for deep learning networks in Simulink models. The generated code calls optimized NVIDIA CUDA libraries, including cuDNN and TensorRT.

You can use the generated CUDA code within Simulink to:

- Speed up the execution of your Simulink model by using NVIDIA GPUs. When you simulate a model that contains a MATLAB Function or Deep Learning Toolbox blocks, the software generates CUDA MATLAB executable (MEX) code from the block and dynamically links the generated code to Simulink.
- Build an executable that you can use for rapid prototyping on NVIDIA GPUs.

For more information, see Deep Learning in Simulink Using Deep Neural Networks Library and Deep Learning in Simulink Using MATLAB Function Block. You can also deploy the Simulink models on embedded NVIDIA GPUs such as Jetson and DRIVE by using the MATLAB Coder Support Package for NVIDIA Jetson and NVIDIA DRIVE Platforms. For more information, see Targeting NVIDIA Embedded Boards.

Simulink Support: SIL, PIL, and external mode simulations

Test numerical equivalence between model components and production code that you generate from the components by using software-in-the-loop (SIL) and processor-in-the-loop (PIL) simulations. With a SIL simulation, you test the behavior of generated source code on development computer. Simulation does not test code compiled for target hardware because code is compiled for the development computer. With a PIL simulation, you test the compiled object code that you intend to deploy on a target hardware by running the object code on real target hardware.

To determine whether model components and generated code are numerically equivalent, compare GPU acceleration and PIL results against normal mode results. For more information, see Numerical Equivalence Testing

Use external mode simulations for rapid prototyping. With external mode simulation, you can:

- Modify or tune block parameters in real time. When you change parameters in your model, Simulink downloads the new values to the executing target application.
- Monitor and save signal data from the executing target application.

For more information, see Parameter Tuning and Signal Monitoring Using External Mode.

Persistent Variables: Create persistent memory on the GPU

In this release, you can use the `coder.gpu.persistentMemory` pragma to allocate a variable as persistent memory on the GPU. The variable must be fixed size and of a data type supported for GPU code generation.

For example, when generating CUDA code for the entry-point function `foo`, the persistent variable `p` is mapped to the GPU as variable with persistent memory.

```
function output = foo(input)
coder.gpu.kernelfun();
persistent p;
if isempty(p)
   p = zeros(1024,1);
end

coder.gpu.persistentMemory(p);
p = p + 1;
output = input + p;
end
```

Wavelet Toolbox Code Generation: Generate code for FFT-based FIR filtering and Short-time Fourier transform functions

In R2020b, you can generate optimized CUDA code for the following additional Wavelet Toolbox toolbox functions.

- `modwt`
- `imodwt`
- `modwtmra`
- `dwt`
- `idwt`
- `dwt2`
- `idwt2`
- `wavedec`
- `wavedec2`
- `mdwtdec`

Deep Learning: Generate code for custom layers

In R2020b, you can generate CUDA code for deep learning networks that have custom deep learning layers. Custom layer code generation supports NVIDIA CUDA deep neural network library (cuDNN) and the NVIDIA TensorRT high performance inference library for NVIDIA GPUs. When targeting the cuDNN library, the code generator supports both row-major and column-major code generation for custom layers. For other usage notes and limitations, see Custom Layers.

To learn how to define custom deep learning layers, see Define Custom Deep Learning Layers (Deep Learning Toolbox) and Define Custom Deep Learning Layer for Code Generation (Deep Learning Toolbox). For an example on how to generate code for a network with custom layers, see Code Generation For Object Detection Using YOLO v3 Deep Learning.

Multi-Input Networks: Generate code for networks that have multiple inputs

In R2020b, you can generate code for networks that have multiple input layers. For information on training multiple input networks, see Multiple-Input and Multiple-Output Networks (Deep Learning Toolbox).

Convolutional Recurrent Neural Networks: Generate code for convolutional LSTM

In this release, you can generate CUDA code for convolutional LSTM networks. Convolutional LSTM is a type of LSTM network that is made up of convolutional and LSTM layers. Such a network is useful for image and video classification applications where you use convolutional layers to extract features from each frame independently. For more information, see Long Short-Term Memory Networks (Deep Learning Toolbox).

Long Short-Term Memory (LSTM) Networks: Generate code for network activations

You can generate code for the `activations` method and compute the network activations for a specific layer of an LSTM network. For example, the following line of code returns the network activations for the sequence or time series data you specify in `sequences` and the layer you specify in `layerIdx`.

```
out = activations(mynet,sequences,layerIdx,'OutputAs','Channels');
```

Workflow improvements

In R2020b, when generating CUDA MEX with GPU Coder, the code generator uses the NVIDIA compiler and libraries included with MATLAB. The CUDA Toolkit installed with MATLAB includes CUDA runtime, cuBLAS, cuFFT, cuSOLVER, cuDNN, and TensorRT libraries. To use CUDA MEX, you must have a compatible C/C++ compiler, a CUDA enabled GPU device and a CUDA compatible graphics driver.

For more information, see Installing Prerequisite Products.

cuFFT Library Support: Improved performance of generated code for fast Fourier transform (FFT) functions

Compared to previous releases, the code generated for FFT functions by using the cuFFT library calls can have improved performance. In R2020b, the software caches multiple cuFFT plans that have the same geometry. Because some cuFFT plans allocate memory on the GPU, caching can improve memory utilization and improve performance for repeatedly running FFT calls.

Deep Learning Networks: Generate code for additional networks

Code generation by using the CUDA Deep Neural Network library (cuDNN) supports these additional pretrained networks:

- `efficientnetb0` – EfficientNet-b0 model network trained on the ImageNet data set.

Code generation by using the NVIDIA TensorRT Library supports these additional pretrained networks:

- `efficientnetb0` – EfficientNet-b0 model network trained on the ImageNet data set.

Code generation by using the ARM Compute Library supports these additional pretrained networks:

- `efficientnetb0` – EfficientNet-b0 model network trained on the ImageNet data set.

For more information, see Supported Networks and Layers.

Deep Learning Layers: Generate code for additional layers

Code generation by using the CUDA Deep Neural Network library (cuDNN) supports these additional layers:

- `focalLossLayer` predicts object classes using focal loss.
- `gruLayer` creates a gated recurrent unit (GRU) that learns dependencies between time steps in time series and sequence data.
- `rcnnBoxRegressionLayer` refines bounding box locations by using a smooth L1 loss function.
- `rpnClassificationLayer` for region proposal networks RPNs.
- `scalingLayer` for actor or critic network.
- `sequenceFoldingLayer` to convert a batch of image sequences to a batch of images.
- `sequenceUnfoldingLayer` to restore the sequence structure of the input data after sequence folding.
- `sigmoidLayer` applies a sigmoid function to its input such that its output is bounded in the interval (0,1).
- `spaceToDepthLayer` permutes the spatial blocks of the input into the depth dimension.
- `softplusLayer` for actor or critic network.

Code generation by using the NVIDIA TensorRT Library supports these additional layers:

- `focalLossLayer` predicts object classes using focal loss.
- `gruLayer` creates a gated recurrent unit (GRU) that learns dependencies between time steps in time series and sequence data.

- `rcnnBoxRegressionLayer` refines bounding box locations by using a smooth L1 loss function.
- `rpnClassificationLayer` for region proposal networks RPNs.
- `scalingLayer` for actor or critic network.
- `sigmoidLayer` applies a sigmoid function to its input such that its output is bounded in the interval (0,1).
- `spaceToDepthLayer` permutes the spatial blocks of the input into the depth dimension.
- `softplusLayer` for actor or critic network.

Code generation for ARM Mali GPUs using the ARM Compute Library supports these additional layers:

- `focalLossLayer` predicts object classes using focal loss.
- `rcnnBoxRegressionLayer` refines bounding box locations by using a smooth L1 loss function.
- `rpnClassificationLayer` for region proposal networks RPNs.
- `scalingLayer` for actor or critic network.
- `sigmoidLayer` applies a sigmoid function to its input such that its output is bounded in the interval (0,1).
- `spaceToDepthLayer` permutes the spatial blocks of the input into the depth dimension.

For more information, see Supported Networks and Layers.

Code generation for additional Computer Vision Toolbox function

- `pcsegdist`

Code generation for additional Signal Processing Toolbox functions

- `fsst`
- `ifsst`
- `filtfilt`

New examples

This release adds the following examples:

- GPU Code Generation for Lane Detection in Simulink – This example shows how to generate CUDA code for a Simulink model that can detect and output lane marker boundaries on an image. This example takes RGB image as an input and uses the `imresize`, `rgb2gray`, `ordfilt2`, `hough`, `houghpeaks`, and `houghlines` functions that are part of Image Processing Toolbox to detect lane markings.
- GPU Code Generation for a Fog Rectification Simulink Model – Demonstrates how to generate CUDA code from the Simulink model that takes a foggy image as input and produces a defogged image as output. This example is a typical implementation of fog rectification algorithm. The example uses `conv2`, `rgb2gray`, and `imhist` functions.
- Code Generation for a Deep Learning Simulink Model to Classify ECG Signals – Shows how you can use powerful signal processing techniques and Convolutional Neural Networks together to classify ECG signals in Simulink. This example also shows how to generate CUDA from the Simulink model.

- Code Generation for a Deep Learning Simulink Model that Performs Lane and Vehicle Detection – Shows how to develop a CUDA application from a Simulink model that performs lane and vehicle detection using convolutional neural networks (CNN). This example takes the frames of a traffic video as an input, outputs two lane boundaries that correspond to the left and right lanes of the ego vehicle, and detects vehicles in the frame.
- Code Generation for Lidar Point Cloud Segmentation Network – Shows how to generate CUDA MEX for a lidar (light detection and ranging) semantic segmentation network that uses deep learning. This example uses the `SqueezeSegV2` network trained to segment organized lidar point clouds belonging to three classes (background, car, and truck). The generated MEX takes a point cloud input and performs prediction on the point cloud by using the `DAGNetwork` object for the `SqueezeSegV2` network.
- Code Generation for a Video Classification Network – Shows how to generate CUDA code for a deep learning network that classifies video and deploy the generated code onto the NVIDIA Jetson Xavier board using the MATLAB Coder Support Package for NVIDIA Jetson and NVIDIA DRIVE Platforms. The deep learning network has both convolutional and bidirectional long short-term memory (BiLSTM) layers. The generated application reads the data from a specified video file as a sequence of video frames and outputs a label that classifies the activity in the video.
- Code Generation For Object Detection Using YOLO v3 Deep Learning – This example shows how to generate CUDA® MEX for a you only look once (YOLO) v3 object detector with custom layers. The example uses YOLO v3 object detection to illustrate:
  - CUDA code generation for a deep learning network with custom layers.
  - Convert a deep learning dlnetwork object into a DAGNetwork object for code generation.

To see the full list of examples for GPU Coder, at the MATLAB command line, enter `doc gpucoder`.

Functionality being removed or changed

`cnncodegen` Function: ARM Mali targets support only
Behavior change in future release

In a future release, the `cnncodegen` function will generate C++ code and build a static library for only the ARM Mali GPU processor. You can continue to use the `'arm-compute-mali'` value for the `'targetlib'` argument to target an ARM Mali GPU by using the ARM Compute Library for computer vision and machine learning.

For all other targets, use the `codegen` command. To learn about targeting cuDNN targets by using the `codegen` function, see Code Generation for Deep Learning Networks by Using cuDNN. To learn about targeting TensorRT targets by using the `codegen` function, see Code Generation for Deep Learning Networks by Using TensorRT.

R2020a

Version: 1.5

New Features

Bug Fixes

Compatibility Considerations

cuBLAS Support: Generate CUDA code for strided and batched matrix multiply

In R2020a, you can generate CUDA code from MATLAB functions to compute many (small) matrix-matrix multiplies at once. This technique is known as batched matrix-matrix multiply can potentially improve device utilization and overall performance.

Use the `gpucoder.batchedMatrixMultiply` function to perform batched matrix multiply operation of the form `D = (alpha*A)xB`.

Use the `gpucoder.batchedMatrixMultiplyAdd` function to perform batched matrix multiply with add operation of the form `D = (alpha*A)xB + (beta*C)`. For example,

```
[D1,D2] = gpucoder.batchedMatrixMultiplyAdd(A1,B1,C1,A2,B2,C2,...
'alpha',0.3,'beta', 0.4,'transpose','TT');
```

You can also perform strided matrix multiplication for matrix batches, where subsequent matrices are memory-contiguous by using the `gpucoder.stridedMatrixMultiply` and `gpucoder.stridedMatrixMultiplyAdd` functions. For example,

```
D = gpucoder.stridedMatrixMultiply(A,B,'alpha',0.4,'transpose','TT');
```

Single Shot Object Detection (SSD) Networks: Object detection on NVIDIA GPU by using a single shot multibox detector

In R2020a, you can generate CUDA code for an SSD network (`ssdObjectDetector` object) and take advantage of the NVIDIA cuDNN and TensorRT libraries.

The SSD detector uses a single stage object detection network that merges detections predicted from multiscale features. The SSD is faster than two-stage detectors, such as the Faster R-CNN detector and can localize objects more accurately compared to single-scale feature detectors such as the YOLO v2 detector. For more information, see Getting Started with SSD Multibox Detection (Computer Vision Toolbox).

For more information on the SSD layers supported in this release, see Supported Networks and Layers. The Code Generation for Object Detection by Using Single Shot Multibox Detector shows how to generate CUDA code for an SSD based vehicle object detector.

Row-Major Array Layout: Simplify interfacing generated deep learning code with target libraries by storing arrays in row-major layout

The code that you generate can store array elements in column-major or row-major array layout. In column-major array layout, the elements of the columns are contiguous in memory. In row-major, the elements of the rows are contiguous. MATLAB uses column-major array layout by default, whereas the deep learning networks supported by NVIDIA cuDNN, TensorRT, and ARM Compute libraries use row-major layout by default.

In previous releases, the code generator produced CUDA C++ code that performed transpose operations on the row-major data and called predict or activation on the transposed data. In R2020a, you can choose to generate code that uses row-major array layout. Row-major layout can improve performance for certain networks and ease integration with other code that also uses row-major layout. For more information, see Array Layout (MATLAB Coder).

For more information on deep learning code generation, see Deep Learning with GPU Coder.

Long Short-Term Memory (LSTM) Networks: Generate code for bidirectional and stateful LSTM

In R2020a, you can generate CUDA code for bidirectional and stateful LSTM networks. A bidirectional LSTM network is a type of recurrent neural network (RNN) that learns bidirectional long-term dependencies between time steps of sequence data. Stateful LSTM networks can remember the state of the network between predictions. The network state can be useful when you do not have the complete time series in advance, or if you want to make multiple predictions on a long time series. For more information, see Long Short-Term Memory Networks (Deep Learning Toolbox).

For a code generation example using stateful LSTM, see Code Generation for a Sequence-to-Sequence LSTM Network

For more information on the LSTM layers supported in this release, see Supported Networks and Layers. Use the `predictAndUpdateState` to predict parts of a time series and update the network state. Use the `resetState` to reset the network state between predictions.

Multi-Output Networks: Generate code for networks with multiple outputs

In R2020a, you can generate code for networks with multiple output layers. For information on training multiple output networks, see Multiple-Input and Multiple-Output Networks (Deep Learning Toolbox).

Deep Learning Networks: Generate code for more networks

In R2020a, you can generate code for networks such as Darknet19, Darknet53, NASNet-Large, NASNet-Mobile, and Inception-ResNet-v2. For more information, see Supported Networks and Layers.

Generate code for half-precision floating point data type

In R2020a, you can generate CUDA code for half-precision floating point data types in MATLAB. Half-precision data types occupy only 16 bits of memory, but their floating-point representation enables them to handle wider dynamic ranges than integer or fixed-point data types of the same size.

For a full list of features that support half-precision code generation, see `half`. For examples that demonstrate half-precision code generation, see Edge Detection with Sobel Method in Half-Precision, Fog Rectification, and Stereo Disparity.

Deep Learning Layers: Generate code for more layers

Code generation with the CUDA Deep Neural Network library (cuDNN) supports these additional layers:

- `anchorBoxLayer` layer to store anchor boxes for object detection.

- Bidirectional long short-term memory (BiLSTM) layer (`bilstmLayer`).
- `concatenationLayer` that concatenates inputs along a specified dimension.
- Flatten layer (`flattenLayer`).
- Global max pooling layer (`globalMaxPooling2dLayer`).
- `ssdMergeLayer` layer to merge activations from several feature maps.
- Word embedding layer for deep learning networks (`wordEmbeddingLayer`).
- Layer that implements ONNX identity operator (`nnet.onnx.layer.IdentityLayer`).

Code generation with the NVIDIA TensorRT Library supports these additional layers:

- `anchorBoxLayer` layer to store anchor boxes for object detection.
- Bidirectional long short-term memory (BiLSTM) layer (`bilstmLayer`).
- `concatenationLayer` that concatenates inputs along a specified dimension.
- Global max pooling layer (`globalMaxPooling2dLayer`).
- Long short-term memory (LSTM) layer (`lstmLayer`).
- Sequence input layer (`sequenceInputLayer`).
- `ssdMergeLayer` layer to merge activations from several feature maps.
- Word embedding layer for deep learning networks (`wordEmbeddingLayer`).
- Layer that implements ONNX identity operator (`nnet.onnx.layer.IdentityLayer`).

Code generation with the ARM Compute Library supports these additional layers:

- `anchorBoxLayer` layer to store anchor boxes for object detection.
- Layer that applies 2-D cropping to the input (`crop2dLayer`).
- Global max pooling layer (`globalMaxPooling2dLayer`).
- Affine layer for the ONNX network that performs element-wise scaling of the input followed by an addition (`nnet.onnx.layer.ElementwiseAffineLayer`).
- Layer that implements ONNX identity operator (`nnet.onnx.layer.IdentityLayer`).

For more information, see Supported Networks and Layers.

Code generation for more MATLAB functions

- `filter`
- `fftshift`
- `circshift`

Code generation for more Image Processing Toolbox functions

- `bwlookup`
- `imrotate`
- `imboxfilt`
- `imgaussfilt`

Code generation for more Computer Vision Toolbox functions

- `disparitySGM`
- `pointCloud`

Code generation for more Signal Processing Toolbox functions

- `fftfilt`
- `stft`
- `istft`

Code generation for Audio Toolbox functions

- `mfcc`

Deep Learning: Generate code that uses newer versions of ARM Compute library

In R2020a, you can generate more efficient C++ code for layers and networks by using version 19.05 of the ARM Compute Library for computer vision and machine learning. To learn more about supported compilers and libraries, see Code Generation for a Sequence-to-Sequence LSTM NetworkInstalling Prerequisite Products. For an example on targeting the ARM Compute Library, see Code Generation for Deep Learning Networks Targeting ARM Mali GPUs.

New and updated examples

This release adds the following examples:

- Code Generation for Object Detection by Using Single Shot Multibox Detector – Shows how to generate CUDA code for an SSD network (ssdObjectDetector object) and take advantage of the NVIDIA cuDNN libraries. An SSD network is based on a feed-forward convolutional neural network that detect multiple objects within the image in a single shot. SSD network can be thought of as having two sub-networks. A feature extraction network, followed by a detection network..
- Edge Detection with Sobel Method in Half-Precision – Demonstrates edge detection in an image with a MEX function generated from a MATLAB function. The edge detection algorithm is implemented with half-precision data type.

This release updates the following examples:

- Code Generation for a Sequence-to-Sequence LSTM Network – demonstrates how to generate CUDA code for a long short-term memory (LSTM) network. The example generates a MEX application that makes predictions at each step of an input time series. Two methods are demonstrated: a method using a standard LSTM network, and a method leveraging the stateful behavior of the same LSTM network. This example uses accelerometer sensor data from a smartphone carried on the body and makes predictions on the activity of the wearer. User movements are classified into one of five categories, namely dancing, running, sitting, standing, and walking.
- Fog Rectification – Shows the use of image processing functions for GPU code generation. This example also shows half-precision code generation using GPU Coder.

- Stereo Disparity – Shows how to generate a MEX function from a MATLAB function that computes the stereo disparity of two images. This example also shows half-precision code generation using GPU Coder.

To see the full list of examples for GPU Coder, at the MATLAB command line, enter `doc gpucoder`.

Functionality being removed or changed

The `coder.checkGpuInstallApp` has been renamed to `gpucoderSetup`.

Compatibility Considerations

Functionality	What Happens When You Use This Functionality?	Use This Instead	Compatibility Considerations
`coder.checkGpuInstallApp`	Still runs	Use `gpucoderSetup`	Replace all instances of `coder.checkGpuInstallApp` with `gpucoderSetup`.

R2019b

Long Short-Term Memory (LSTM) Networks: Generate code for recurrent networks such as LSTM

In R2019b, you can generate CUDA code for an LSTM network and take advantage of the NVIDIA cuDNN library. An LSTM network is a type of recurrent neural network (RNN) that can learn long-term dependencies between time steps of sequence data. For more information on the LSTM layers supported in this release, see Supported Networks and Layers.

Deep Learning Targeting: Deploy deep learning networks to ARM Mali GPU processors

You can generate code for prediction from a pretrained convolutional neural network (CNN) and target the code to an embedded platform that uses an ARM Mali GPU processor. The code generator takes advantage of ARM Compute Library for computer vision and machine learning. The generated code implements a CNN that has the architecture, layers, and parameters specified in the input `SeriesNetwork` or `DAGNetwork` objects. For more information, see Code Generation for Deep Learning Networks Targeting ARM Mali GPUs.

For information on the networks and layers supported for code generation, see Supported Networks and Layers.

TensorRT Support: Support for NVIDIA TensorRT library on the Windows platform

In R2019b, you can take advantage of the NVIDIA low-latency, high-throughput TensorRT inference library for your deep learning applications and generate CUDA code on the Windows® platform. For information on the supported TensorRT version, see Installing Prerequisite Products. To set up your development computer for code generation, see Setting Up the Prerequisite Products. To generate CUDA code targeting the TensorRT libraries, see Code Generation for Deep Learning Networks by Using TensorRT.

Deep Learning Networks: Generate code for more networks

In R2019b, you can generate code for networks such as DeepLab-v3+, MobileNet-v2, ONNX™ (Open Neural Network Exchange), and Xception. For more information, see Supported Networks and Layers.

Deep Learning Layers: Generate code for more layers

Code generation with the CUDA Deep Neural Network library (cuDNN) supports these additional layers:

- Pixel classification layer by using generalized dice loss for semantic segmentation (`dicePixelClassificationLayer`)
- Exponential linear unit (ELU) layer (`eluLayer`)
- 2-D grouped convolutional layer (`groupedConvolution2dLayer`)
- Long short-term memory (LSTM) layer (`lstmLayer`)
- All output layers including custom classification or regression output layers created by using `nnet.layer.ClassificationLayer` or `nnet.layer.RegressionLayer`

- Sequence input layer (`sequenceInputLayer`)
- Hyperbolic tangent (tanh) layer (`tanhLayer`)
- Affine layer for the ONNX network that performs element-wise scaling of the input followed by an addition (`nnet.onnx.layer.ElementwiseAffineLayer`)
- Flatten layer for the ONNX network that flattens the spatial dimensions of the input tensor to the channel dimensions (`nnet.onnx.layer.FlattenLayer`)

Code generation with the NVIDIA TensorRT Library supports these additional layers:

- Clipped rectified linear unit (ReLU) layer (`clippedReluLayer`)
- Pixel classification layer using generalized dice loss for semantic segmentation (`dicePixelClassificationLayer`)
- Exponential linear unit (ELU) layer (`eluLayer`)
- 2-D grouped convolutional layer (`groupedConvolution2dLayer`)
- All output layers including custom classification or regression output layers created by using `nnet.layer.ClassificationLayer` or `nnet.layer.RegressionLayer`
- Hyperbolic tangent (tanh) layer (`tanhLayer`)
- Flatten layer for the ONNX network that flattens the spatial dimensions of the input tensor to the channel dimensions (`nnet.onnx.layer.FlattenLayer`)

For more information, see Supported Networks and Layers.

1-D reduction operations on the GPU

In R2019b, you can use the `gpucoder.reduce` function to generate CUDA code that performs efficient 1-D reduction operations on the GPU. The generated code uses the CUDA shuffle intrinsics to implement the reduction operation.

For example, to find the `sum` and `max` elements of an array `A`:

```
function s = myReduce(A)
   s = gpucoder.reduce(A, {@mysum, @mymax});
end

function c = mysum(a, b)
   c = a+b;
end

function c = mymax(a, b)
   c = max(a,b);
end
```

For code generation, the `gpucoder.reduce` function has these requirements:

- The input must be of numeric or logical data type.
- The function passed through the @handle must be a binary function that accepts two inputs and returns one output. The inputs and outputs must be of the same data type.
- The function must be commutative and associative.

Workflow and generated code improvements

R2019b includes the following improvements in the generated code:

- Performance improvement in the code generated for the `cumsum` function.
- Variables and expression support for specifying dimensions in the kernel pragmas. For more information, see `coder.gpu.kernel`.

Code generation for more Image Processing Toolbox functions

- `bwconncomp`
- `bwlabel`
- `houghlines`
- `imadjust`
- `imhist`
- `imfill`
- `imreconstruct`

Code generation for more MATLAB functions

- `interp2`
- `min`
- `max`
- `rgb2gray`

Code generation for more Computer Vision Toolbox functions

- `selectStrongestBboxMulticlass`

Functionality being removed or changed

This release removes support for generating CUDA code by using CUDA Toolkit version 8.

Compatibility Considerations

GPU Coder throws an error if the supported CUDA Toolkit is not found on the development platform. For information on the supported compilers and libraries, see Installing Prerequisite Products.

New examples

This release adds the following examples:

- Code Generation for a Sequence-to-Sequence LSTM Network – Shows how to generate CUDA code for a long short-term memory (LSTM) network. The example generates a MEX application that makes predictions at each step of an input time series. This example uses accelerometer sensor data from a smartphone carried on the body and makes predictions on the activity of the

wearer. User movements are classified into one of five categories, namely dancing, running, sitting, standing, and walking.

- Deep Learning Prediction on ARM Mali GPU– Shows how to use the `cnncodegen` function to generate code for an image classification application that uses deep learning on ARM Mali GPUs. The example uses the MobileNet-v2 DAG network to perform image classification.
- QR Decomposition on an NVIDIA GPU Using cuSOLVER Libraries– Shows how to create a standalone CUDA executable that leverages the CUDA Solver library (cuSOLVER). The example uses a curve fitting application that mimics automatic lane tracking on a road to illustrate several topics, including:
  - Fitting an arbitrary-order polynomial to noisy data using matrix QR factorization.
  - Using the `coder.LAPACKCallback` class to provide the LAPACK library information for the code generator when generating standalone executables.
- Lane Detection on the GPU using `houghlines`– Shows how to generate CUDA MEX for a MATLAB function that can detect and output lane marker boundaries on an image. The example takes an RGB image as input and uses the `rgb2gray`, `ordfilt2`, `hough`, `houghpeaks`, and `houghlines` functions that are part of Image Processing Toolbox to produce the lane detected output image.

To see the full list of examples for GPU Coder, at the MATLAB command line, enter `doc gpucoder`.

R2019a

Version: 1.3

New Features

Bug Fixes

Deep Learning: Generate code for more layers

Code generation with the CUDA Deep Neural Network library (cuDNN) supports these additional layers:

- Layer that applies 2-D cropping to the input (`crop2dLayer`)
- One of the layers that allows the network to use features from earlier by making the features match the feature map size at the later layer (`YOLOv2ReorgLayer`)
- Output layer for YOLO v2 object detection network (`YOLOv2OutputLayer`).
- Transform layer for YOLO v2 object detection network (`YOLOv2TransformLayer`).
- Flatten activations into 1-D assuming C-style (row-major) order (`nnet.keras.layer.FlattenCStyleLayer`)
- Global average pooling layer for spatial data (`nnet.keras.layer.GlobalAveragePooling2dLayer`)
- Sigmoid activation layer (`nnet.keras.layer.SigmoidLayer`)
- Hyperbolic tangent activation layer (`nnet.keras.layer.TanhLayer`)
- Zero padding layer for 2-D input (`nnet.keras.layer.ZeroPadding2dLayer`)

Code generation with the NVIDIA TensorRT Library supports these additional layers:

- Layer that applies 2-D cropping to the input (`crop2dLayer`)
- Depth concatenation layer (`depthConcatenationLayer`)
- One of the layers that allows the network to use features from earlier by making the features match the feature map size at the later layer (`YOLOv2ReorgLayer`)
- Output layer for YOLO v2 object detection network (`YOLOv2OutputLayer`).
- Transform layer for YOLO v2 object detection network (`YOLOv2TransformLayer`).
- Flatten activations into 1-D assuming C-style (row-major) order (`nnet.keras.layer.FlattenCStyleLayer`)
- Global average pooling layer for spatial data (`nnet.keras.layer.GlobalAveragePooling2dLayer`)
- Sigmoid activation layer (`nnet.keras.layer.SigmoidLayer`)
- Hyperbolic tangent activation layer (`nnet.keras.layer.TanhLayer`)
- Zero padding layer for 2-D input (`nnet.keras.layer.ZeroPadding2dLayer`)

For more information on supported networks and layers, see Supported Networks and Layers.

TensorRT Support: Generate code that takes advantage of FP16 optimization in deep learning inference applications

Using TensorRT half-precision (also called FP16) arithmetic support in GPU Coder, the generated neural network code utilizes reduced memory usage compared to FP32 precision. This enables deployment of larger networks while taking less time than FP32. To enable half-precision, set the `DataType` property of the `coder.TensorRTConfig` object to `'fp16'`. Alternatively, you can also set the `DataType` property in the `Deep Learning` settings tab of the GPU Coder App.

Deep Learning: Generate code for more networks

In R2019a, you can generate code for networks such as fully convolutional neural networks (FCN), YOLOv2, and segmentation networks such as U-Net. For more information, see Deep Learning with GPU Coder.

CUDA optimized transpose function

In this release, you can use the `gpucoder.transpose` or `gpucoder.ctranspose` functions to perform efficient out-of-place non-conjugate or conjugate transpose on the GPU. This implementation uses shared memory for improved performance. For example,

```
A = rand(5,10);
B = gpucoder.transpose(A);
```

This function must not be used for inputs whose dimensions are greater than 2.

Support for unbounded variables

In this release, GPU Coder supports CUDA code generation for MATLAB code that contains unbounded variables.

Workflow and generated code quality improvements

R2019a includes these workflow and generated code quality improvements:

- Verify and set up the GPU code generation environment by using the `coder.checkGpuInstallApp`. The **Check GPU Install** app is an interactive tool to verify and set up the GPU code generation environment on your development computer and hardware platforms such as the NVIDIA DRIVE and Jetson. For more information, see Using the Check GPU Install App.

  You can also use the `coder.checkGpuInstall` function to perform the same checks from the MATLAB command line. In this release, the `coder.checkGpuInstall` function has been updated to accept a `coder.gpuEnvConfig` object. The `coder.gpuEnvConfig` object contains the configuration parameters that `coder.checkGpuInstall` uses to verify the GPU code generation environment. You can continue to use option flags with the `coder.checkGpuInstall` as in previous releases, but it is recommended to use the `coder.gpuEnvConfig` object as this functionality may be deprecated in a future release.
- Improved handling for loops with dynamic bound variables.
- CUDA profiling integration with the SIL interface.
- Support for the `gpuArray` function when performing SIL simulation.

Code generation for more MATLAB functions

- `conv`

Code generation for more Image Processing Toolbox functions

- `hough`
- `houghpeaks`
- `ordfilt2`

Code generation for more Computer Vision Toolbox functions

- `rectifyStereoImages`

Code generation for Statistics and Machine Learning Toolbox functions

In R2019a, you can generate optimized CUDA code for `pdist` and `pdist2` functions from the Statistics and Machine Learning Toolbox™. The supported distance input argument values are `'euclidean'`, `'squareeuclidean'`, `'seuclidean'`, `'cityblock'`, `'minkowski'`, `'chebychev'`, `'cosine'`, `'correlation'`, `'hamming'`, and `'jaccard'`.

Code generation for Wavelet Toolbox function

In R2019a, you can generate optimized CUDA code for the `cwt` Wavelet Toolbox function. For more information, see Supported Functions.

New examples

This release adds the following examples:

- Train and Deploy Fully Convolutional Networks for Semantic Segmentation – Shows how to train and deploy a fully convolutional semantic segmentation network on an NVIDIA GPU by using GPU Coder.
- Code Generation for Semantic Segmentation Network using U-net – Demonstrates code generation for an image segmentation application that uses U-Net, a popular deep learning network for image segmentation.
- Code Generation for Object Detection Using YOLO v2 – Demonstrates code generation for an object detector using a deep learning technique named you only look once (YOLO) v2.
- Top-Hat Filtering on Jetson TX2– Demonstrates code generation for a top-hat filtering application that removes uneven background illumination on NVIDIA Jetson TX2. This example requires the MATLAB Coder Support Package for NVIDIA Jetson and NVIDIA DRIVE Platforms.
- Deployment and Classification of Webcam Images on NVIDIA Jetson TX2 Platform– Demonstrates deployment and classification of webcam Images on NVIDIA Jetson TX2 Platform. This example requires the MATLAB Coder Support Package for NVIDIA Jetson and NVIDIA DRIVE Platforms.
- Edge Detection on GPU using Order statistic filters– Demonstrates code generation for edge detection algorithm on the GPU using order statistic filters.
- Image Denoising on the GPU using Median filter– Demonstrates code generation for an image denoising application on the GPU using median filter.

To see the full list of examples for GPU Coder, at the MATLAB command line, enter `doc gpucoder`.

R2018b

Deep Learning Retargetability: Deploy applications that use deep learning networks onto Intel MKL-DNN, and NVIDIA TensorRT by using the codegen function

When targeting Intel® MKL-DNN, and NVIDIA TensorRT libraries, GPU Coder now supports code generation for deep learning networks by using the `codegen` function. In previous releases, you could use the `codegen` function to target only NVIDIA cuDNN libraries.

To use the `codegen` function, create a GPU configuration object and set the `DeepLearningConfig.TargetLib` property to `'cudnn'`, `'mkldnn'`, or `'tensorrt'`. For more information, see Code Generation for Deep Learning Networks with TensorRT and Code Generation for Deep Learning Networks with MKL-DNN (MATLAB Coder).

Compatibility Considerations

In R2018b, you must install the MATLAB Coder Interface for Deep Learning and GPU Coder Interface for Deep Learning to generate code for deep learning networks.

In previous releases, you could target NVIDIA cuDNN libraries without specifying a target library in the code configuration object. In R2018b, you must set the `cfg.DeepLearningConfig = coder.DeepLearningConfig('cudnn')` configuration object to target cuDNN libraries.

Thrust Library Support: Generate GPU-accelerated code for sort and reduction operations by using the Thrust library

With Thrust library support in GPU Coder, you can take advantage of GPU-accelerated primitives such as sort to implement complex high-performance parallel applications. When your MATLAB code uses `gpucoder.sort` function instead of `sort`, GPU Coder can generate calls to the Thrust sort primitives. For more information, see Thrust Example.

Deep Learning Optimization: Improve performance and memory utilization through auto-tuning, layer fusion, and buffer minimization

When generating code for deep learning networks by using the cuDNN libraries, you can now take advantage of the auto-tuning functionality in the library to select an optimal convolutional algorithm. The convolutional algorithm selection is based on the input, kernel sizes, and memory availability resulting in improved performance. To control the auto-tuning functionality, use the `DeepLearningConfig.AutoTuning` property of the GPU code configuration object. This capability is available only when targeting cuDNN libraries and is enabled by default. For more information, see `coder.CuDNNConfig`.

In R2018b, the code generator uses layer fusion and double buffering techniques to generate optimized code for deep learning networks.

- Convolutional and Rectified Linear Unit (ReLU) layers are fused into `FusedConvRelu` layer.
- Convolutional and Batch normalization layers are also fused to a `convolutional` layer with modified weights and biases.
- Convolutional, Batch normalization layer, and Rectified Linear Unit (ReLU) layers are also fused as `FusedConvRelu` layer.

gpuArray Support: Use gpuArray arguments at the I/O of MEX targets

In R2018b, you can use `gpuArray` arguments as inputs and outputs to an entry-point function when generating CUDA MEX code. Because the `gpuArray` function copies the array to the GPU, the generated code contains fewer `cudaMemcpy` calls. To use this functionality, use `coder.Type` to represent the `gpuArray` type of an entry-point function input. For example, you can use `coder.typeof(rand(20),'Gpu',true)` or `coder.typeof(gpuArray(rand(20)))` to create a `gpuArray` type for code generation.

Support Package for NVIDIA GPUs: Target NVIDIA Jetson and DRIVE platforms

In R2018b, you can use the MATLAB Coder Support Package for NVIDIA Jetson and NVIDIA DRIVE Platforms to communicate with, deploy, and run CUDA code on NVIDIA platforms such as Jetson and DRIVE. To download the support package, use the Add-on Explorer. For more information on the supported workflows, see GPU Coder Support Package for NVIDIA GPUs.

Calling External CUDA Functions: Use GPU arguments that pass by reference when using coder.ceval

In R2018b, you can pass GPU arguments by reference when calling external CUDA functions with `coder.ceval`. To make `coder.ceval` pass arguments by reference, use the constructs `coder.ref`, `coder.rref`, and `coder.wref`.

Deep Learning Layers: Generate code for new network layers

In R2018b, you can now generate code for these layers:

- Dilated convolutional
- Variable-size I/O

Ease-of-use and traceability improvements

This release contains a new traceability report that highlights sections of MATLAB code that are running on the GPU, a new diagnosis report to analyze performance breakdown, and an integrated GPU profiling report to analyze execution profiles of the generated code.

You can use the traceability feature to understand how the code generator maps your algorithm to GPU kernels, debug issues in the generated code, and evaluate the quality of the generated code. For more information on using the traceability feature, see Trace Between MATLAB Code and Generated CUDA Code.

In R2018b, the code generation report has a new diagnostic section that analyzes performance issues with your MATLAB algorithm and categorizes them as kernel issues, memory issues, pragma issues, and design pattern issues. The report provides suggestions for resolving the issues so that you can generate more efficient CUDA code. To enable report generation, set the `GenerateReport` property in the code configuration object or enable the **Always create a code generation report** option in **More Settings ->Debugging** pane of the GPU Coder app.

For information on the GPU profiling report, see Analyze Execution Profiles of the Generated Code.

In R2018b, CUDA syntax highlighting in the MATLAB editor helps you identify the different CUDA language elements in the generated code. You can change syntax highlighting preferences. On the **Home** tab, in the **Environment** section, click **Preferences**. Select **MATLAB > Editor/Debugger > Language > CUDA**.

Code generation for more Image Processing Toolbox functions

In R2018b, you can generate optimized CUDA code for the `imresize` Image Processing Toolbox function. For more information, see Supported Functions.

Deep learning examples

This release adds two deep learning examples:

- Integrating Deep Learning with GPU Coder into Simulink – Demonstrates integration of the CUDA code generated for a deep learning network into the Simulink environment.
- Code Generation for Denoising Deep Neural Network – Shows how to generate CUDA code for a denoising convolutional neural network (DnCNN). You can use the denoising network to estimate noise in a noisy image, and then remove it to obtain a denoised image.
- Deep Learning Prediction with NVIDIA TensorRT – Shows how to generate CUDA code by using the TensorRT library.
- Deep Learning Prediction with Different Batch Sizes – Shows how to use different batch sizes when generating code for a deep learning network.

To see the full list of examples for GPU Coder, at the MATLAB command line, enter gpucoderexamples.

Functionality being removed or changed

Compatibility Considerations

- Specifying the C language for the generated code through the `TargetLang` property of `coder.config` will be removed in a future release.

Functionality	What Happens When You Use This Functionality?	Use This Instead
`TargetLang = 'C'` property of `coder.config` object.	You get a warning message.	`TargetLang = 'C++'` property of `coder.config` object.

- To perform code generation for deep learning networks, you must install the `GPU Coder Interface for Deep Learning Libraries` and `MATLAB Coder Interface for Deep Learning Libraries` support packages. To install these support packages, select the support package from the MATLAB **Add-Ons** menu.

Functionality	What Happens When You Use This Functionality?	Solution
Using `cnncodegen` or `codegen` functions to generate code for deep learning networks.	You get an error message.	To install the required support packages, follow the links in the error message.

R2018a

Version: 1.1

New Features

Bug Fixes

Directed Acyclic Graph (DAG) Networks: Generate CUDA code for deep learning networks with DAG topology

You can use GPU Coder in tandem with the Neural Network Toolbox™ to generate CUDA code for DAG networks. A DAG network is a neural network for deep learning that can have its layers arranged as a directed acyclic graph. You can use a pretrained DAG network or train one by using the Neural Network Toolbox. See, Supported Networks and Layers.

Deep Learning Layers: Generate CUDA code for popular networks such as GoogLeNet, ResNet, and SegNet

In R2018a, you can target generate CUDA code for popular convolutional neural networks such as GoogLeNet, ResNet, and SegNet. See, Supported Networks and Layers

TensorRT Support: Generate code that takes advantage of NVIDIA deep learning inference optimizer and run time

With TensorRT support in GPU Coder, you can take advantage of the NVIDIA low-latency, high throughput inference library for your deep learning applications on embedded platforms. For more information, see CNN Code Generation, and `cnncodegen`.

Multi-Platform Deep Learning Targeting: Deploy deep learning networks to Intel and ARM processors

Generate code that takes advantage of Intel Math Kernel Library for Deep Neural Networks (MKL-DNN) for Intel CPUs, and ARM Compute libraries for mobile platforms. For more information, see CNN Code Generation.

Code generation for Image Processing Toolbox functions

In R2018a, you can generate optimized code for Image Processing Toolbox functions such as `imerode`, `imdilate`, and `imwarp`. For more information, see Supported Functions.

Code generation for Computer Vision System Toolbox functions

Generate optimized CUDA code for the `matchfeatures` function. For more information, see Supported Functions.

Loop and kernel optimization

In R2018a, you can map while loops and dynamically bound for-loops to GPU kernels. This feature allows you to generate CUDA code containing kernels with variable and symbolic dimensions.

Deep learning examples

This release adds three deep learning examples:

- Pedestrian Detection – Demonstrates code generation for a pedestrian detection implementation that has several applications in the fields of autonomous driving, surveillance, and robotics.

- Traffic Sign Detection and Recognition – Demonstrates how to generate CUDA MEX code to detect traffic signs, suppress overlapping detections, and classify the detected traffic signs.
- Logo Recognition Network – Demonstrates code generation for a logo classification application that can recognize 32 logos under various lightning conditions and camera motions.

Use gpucoderexamples to see the full list of examples that ship with GPU Coder.

R2017b

Version: 1.0

CUDA C and C++ code Generation

Generate CUDA C and C++ code from MATLAB code. You can integrate the generated code into your project as source code, static libraries, or dynamic libraries. The generated code calls optimized NVIDIA CUDA libraries, including cuDNN, cuSolver, cuFFT, and cuBLAS. To generate CUDA code, you must have the following products:

- MATLAB
- GPU Coder
- MATLAB Coder
- Parallel Computing Toolbox™

For more information, see Getting Started with GPU Coder.

Deep Learning Network Support

You can use GPU Coder in tandem with the Neural Network Toolbox to generate CUDA code for deep learning networks. You can use the Neural Network Toolbox to create and train a neural network, or import pretrained networks like VGG, MNIST, AlexNET, YOLO. See, Deep Learning.

Image Processing Toolbox Support

GPU Coder supports CUDA code generation for many of the functions from MATLAB and the Image Processing Toolbox.

CUDA Kernel and memory Optimizations

GPU Coder performs program parallelism analysis to identify segments of code that run on the CPU and segments that run on the GPU. After this kernel partitioning and optimization is complete, GPU Coder performs memory optimization by analyzing the data dependency between the CPU and GPU partitions. GPU Coder also provides you pragmas and design patterns that can be used to generate optimized CUDA code.

MEX Function Generation for code Verification and Acceleration

With GPU Coder, you can also use the generated code within the MATLAB environment to accelerate computationally intensive portions of your MATLAB code. MEX functionality also allows you to verify the numerical correctness of the generated code.

Legacy CUDA code Integration

If you have highly optimized CUDA code for certain subfunctions that you want to incorporate into your generated code, GPU Coder extends the `coder.ceval` functionality to help you achieve this goal.

Hardware Integration with NVIDIA Tegra

You can use GPU Coder to generate CUDA code for targeting embedded GPU platforms. Specifically, you can target the NVIDIA Tegra® development boards Jetson TK1, TX1, and TX2 on either Windows or Linux® systems.

Code Profiling and Verification

By using GPU Coder with Embedded Coder®, you can verify the numerical behavior of the generated C/C++ code by using software-in-the-loop (SIL) execution.