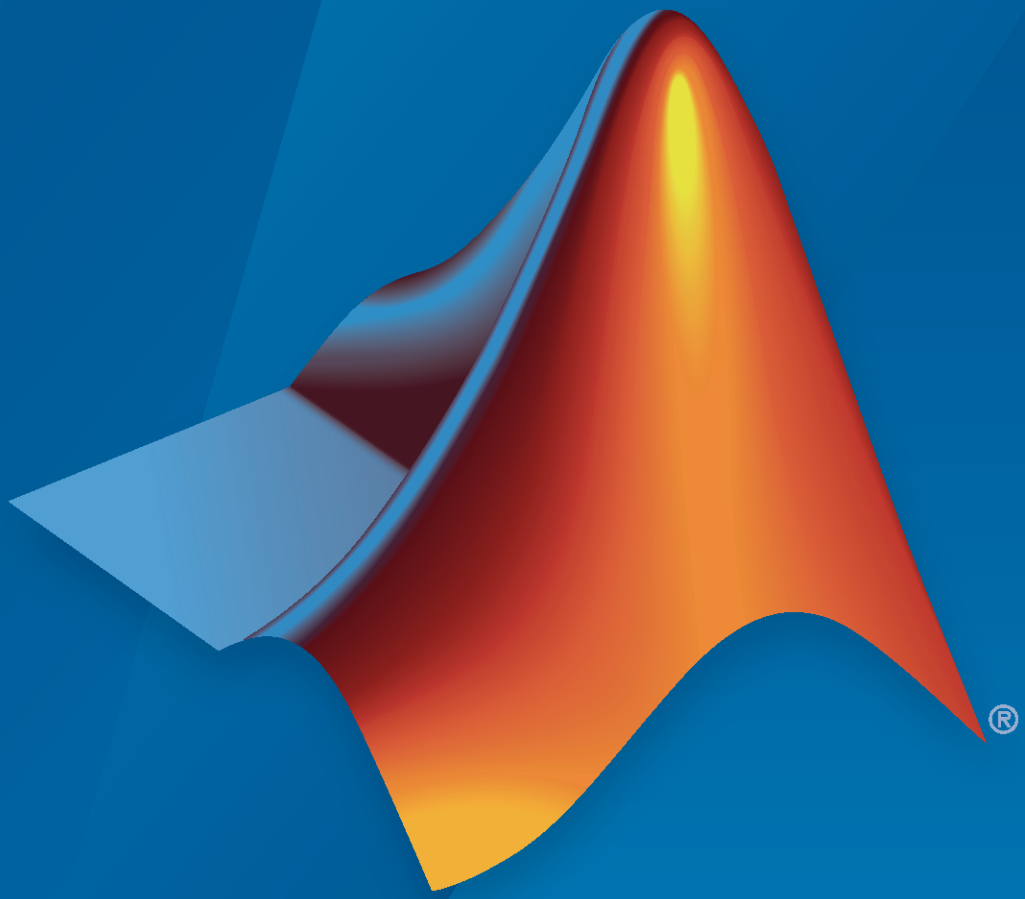
GPU Coder™ Release Notes



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GPU Coder™ Release Notes

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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 Network”“Installing 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 GPU Coder Support Package for NVIDIA GPUs.
- 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 GPU Coder Support Package for NVIDIA GPUs.
- 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

Version: 1.2

New Features

Bug Fixes

Compatibility Considerations

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 Libraries and GPU Coder Interface for Deep Learning Libraries 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 GPU Coder Support Package for NVIDIA GPUs 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 **Miore 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 CUDAcode 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.