Open Neural Network Exchange (ONNX) Support for Julia Developers

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Abstract

Developers often have to stick to a single programming language and framework for their Deep Learning projects. Sharing pre-trained models between frameworks is a tedious task, requiring the preservation of the structure of the neural network, as well as its individual layers and parameters. We developed **KnetOnnx.jl**, a software package in Julia that makes use of the Open Neural Network Exchange (ONNX) Format to automate this process, giving Julia developers the tools to read ONNX files and re-construct the corresponding models in Knet. Given the ONNX representation of a model, we provide the user with a Knet Model that can be re-designed, re-trained or simply used for inference. Our current build can convert all multi-input & multi-output graphical models, as long as the operators are supported by ONNX and the package. We hope that this technical report will also serve as a reference to developers who wish to make their Deep Learning Framework compatible with ONNX.

1 Introduction

Due to the immense number of tools, frameworks and programming languages that are being used in the field of Machine Learning, transferring pre-trained models from one framework to another is a tedious task. This difficulty consists of two sub-problems: (1) different implementations of the same model in distinct languages & frameworks, and (2) sharing the parameters of the model such that when they are read into the target environment, we know which layer a certain parameter belongs to, and that it is implemented by the right data structure so that the model functions as intended. Although there has been many attempts by the community to ameliorate the problem of sharing weights, Open Neural Network Exchange (ONNX) is the largest open ecosystem so far that aims to finally solve both problems.

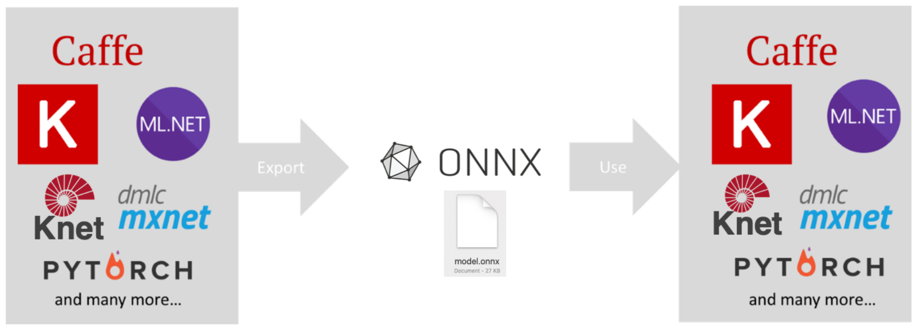


Figure 1: Import & Export

1.1 Open Neural Network Exchange Format

Deep learning models make their prediction through a computation over dataflow graphs. The idea is that if there was a universal representation of neural networks, independent of the programming language (or specific implementation) that is being used, one could always represent their neural network in that format. ONNX provides that intermediate representation we are looking for, capturing the essential properties of a neural network such as its inputs, outputs, structure and also information regarding each individual layer that the neural network consists of. More specifically, it provides (1) a definition of an extensible computation graph model, (2) definitions of standard data types and (3) definitions of built-in operators. Once we have a fixed format for representation, each Deep Learning Framework ought to provide the import and export functionality. The export function takes a model implemented in Framework X, and constructs a representation of it using the ONNX guideline and creates the file: model.onnx. The import function handles the other direction, by reading an ONNX file and implementing the corresponding model in Framework X. Once a framework implements both functions, it is ONNX-complete; meaning that the developer can transfer their model to another ONNX-complete framework Y (and vice versa).

1.2 The ONNX Graph

The ONNX Graph is structured as a list of nodes that form an acyclic graph. Each **node** of the graph represents one of the built-in operators and its attributes. To give an example, a node could be the Convolution operation, and its attributes would contain information regarding the padding and stride that must be used. Every framework supporting ONNX will provide implementations of these operators on the applicable data types. Each edge of the graph represents a piece of data. So the input to the Convolution operation might be a tensor with the name: ”input1”. As a side note, the nodes contain the names of the incoming and outgoing edges (names of the tensors), so it is sufficient to only process the nodes. The graph also has metadata to help document its name, purpose, author, etc.

Finally, the ONNX Graph has the field: **initializer**, which is a dictionary from the names of the parameters to their actual values. In order to preserve the parameters of the original model, the target framework must use these values to initialize individual layers. So the Convolution layer corresponding to a node should be initialized by first looking at the name of its parameters, then using the initializer to get the values of the parameters.

2 System Design

The current version of our software package (KnetOnnx v0.1.0) only provides the import functionality, and the export function is currently left as future work. Let us motivate the design of our system by first dividing to its sub-components the work that must be done by a successful import function. The system must first read the ONNX file and create a graph in Julia. This is done by our ONNX Reader (subsection 2.1). Once the graph is acquired in Julia, a program should iterate over all nodes and create the corresponding layer by using the information stored in the nodes. This is achieved with the use of operator-specific converters (subsection 2.2). In order to create the corresponding layers in Knet, we also need those layers to be implemented in Julia. Since Knet does not currently have a complete library of layers, we had to construct our own mini library of layers (subsection 2.3). Finally, we designed a Knet Model class which would be the model we return to the user (subsection 2.4).

2.1 ONNX Reader

An ONNX file is a Google Protobuf binary file. A Protocol Buffer is a language-neutral, platform-neutral, extensible way of serializing structured data for use in communications protocols, data storage, and more [1]. In order to extract the information, we made use of a Julia Package called ProtoBuf.jl. The resulting piece of data is composed of data structures that are not native to Julia, so we created our own Graph class and converted Proto objects to Julia types. The resulting Graph is easy to read, process and print. The code can be found in the graph directory of our source code.

2.2 Converters

A converter looks at the representation of an operator as specified by the Julia Graph (the output of our ONNX reader), and returns the implementation of that layer in Julia. There is a unique converter for each operator, since they all have different attributes that must be specifically processed to create the correct layer. We make use of a general-purpose **convert** function that takes as input the entire Julia graph and iterates over all nodes one by one. After determining the type of the operation specified by a node, it calls the unique converter for that specific type. All the resulting layers are collected in a list, which will later be used to create a Knet Model. If the converter for an operation does not yet exist the convert function throws an error, notifying the user that the model cannot be re-constructed due to that certain operation. In order to add a new converter, one must first ensure that there exists a Knet Layer that can be used to implement that layer in Julia.

2.3 Knet Layers

Currently Knet does not provide a complete library of neural network layers. It provides a variety of operations like convolution or pooling; but the user must define their own layers by using these more primitive operations. KnetLayers.jl was developed by Ekin Akyürek to address this issue [2], but it only covers a tiny set of operators that an ONNX-complete framework must implement. We still greatly appreciate Ekin's effort, since our own Layer library is built on top the latest version of KnetLayers.jl by simply adding new layers as needed. Please realize that to make our package support some operation O, we need to add two components to our package: (1) A KnetLayer of type K that implements operation O, and (2) a converter that looks at the node which represents an instance of O with certain attributes, and constructs a K object with those attributes. Once the KnetLayer is implemented successfully, implementing the converter for an operation amounts to gathering the parameters (if there are any) from the graph's initializer, the attributes from the node itself, and calling the corresponding KnetLayer constructor with the right arguments. In our current build, we also return the local inputs and outputs of a node (which are the names of incoming & outgoing tensors) to make the forward pass of Knet Model faster.

2.4 Knet Model

Knet Model is what our system returns as its final output to the user. It can be thought of as an implementation of a computational graph where each node is a Model Layer. A Model Layer is nothing but a KnetLayer, accompanied by the names of the input tensors going in and the names of the output tensors going out of that layer. That's why the **layers** field of the Knet Model contains all information regarding all layers and their local connections. The Knet Model also stores the names of the inputs and the outputs of the entire model, so that we know which tensors to return to the user when a forward pass is completed.

So where are all these tensors stored? The final field of the Knet Model is **tensors**, a Julia dictionary that maps tensor names to actual tensors. When a model is created, all tensors are initialized to null values. When the forward function of a Knet Model is called, the input tensors given as arguments to the forward function are placed into the tensors dictionary. Then, we start the process of randomly picking a layer and computing its output. A layer's output can be computed only if its inputs are already computed, so we repeat this process until all tensors are calculated. Once a valid path is found, it is saved to be used in further forward calculations. This process might be replaced by a smarter algorithm in the future, but currently is not necessary since the path is computed only once, before the first forward pass.

3 Analysis & Results

3.1 Operators

An ONNX-complete framework must support all operators that are specified by ONNX [3]. Although we are still working towards that goal, here is a list of operators that our current build supports by providing a KnetLayer implementation, and a converter for their nodes in an ONNX graph.

1. ReLU
2. LeakyReLU
3. Conv
4. MaxPool
5. Dropout
6. Flatten
7. Gemm
8. Add
9. BatchNormalization
10. ImageScaler
11. RNN
12. Unsqueeze
13. Squeeze
14. Concatenate
15. ConstantOfShape
16. Shape
17. Constant

3.2 Models

In our proposal we specified a list of models that we were planning to make sure our software package can read and re-construct without error. We are pleased to report that they have all been copied over successfully, and their demos can be found on our repository's demo section. We also show that the Knet Model can be trained on the MNIST dataset successfully, by copying over a Convolutional Neural Network from PyTorch using ONNX and re-training it on Knet.

1. Multilayer Perceptron (MNIST Demo) [4]
2. Multiple-input, Single-output models [5]
3. Single-input, Multiple-output models [6]
4. Multiple-input, Multiple-output models [7]
5. Branching Models [8]
6. Convolutional Neural Network (MNIST Demo) [9]
7. Recurrent Neural Networks [10]
8. VGG-16 [11]

Models listed above were crucial as a success metric, and it also shows our order of implementation and testing. Copying over a Mutlilayer Perceptron requires that the ONNX Reader, Parameter Trasnfer and two types of Knet-Layers and converters work as intended. A successful copy of a Multiple-input, Multiple-output model requires that the KnetModel knows which tensors to treat as inputs and which tensors to return as outputs. A branching model is any model where at least one layer has more than one output, and each output is input to a different layer. We have experimented with models with multiple branches, and shown that the Knet Model can always find a valid path and that the forward computation halts when all local computations are over. Convolutionals Neural Networks, Recurrent Neural Networks and VGG-16 were also tested to show that our package can handle certain operations that popular deep learning models usually make use of.

4 Conclusion

We believe that KnetONNX.jl is a software package that has the potential to be used by many Julia developers who wish to read ONNX files in Julia or simply transfer their models over to Knet. If further-developed and advertised, it could help Julia and Knet gain new users.

In terms of future work, we must first address the elephant in the room: the export function. The harder solution would be to do it as PyTorch does, by running a dummy input through any function and identifying the operations that are being used; and writing that to a binary protobuf file. The easier but less general solution would be to handle each KnetLayer separately, by writing a KnetLayer to ONNX node converter one by one. This would only handle models that are Knet Models, since the graph structure would be extracted from our Model Layers.

References

[1] developers.google.com/protocol-buffers/docs/overview

[2] github.com/ekinakyurek/KnetLayers.jl

[3] github.com/onnx/onnx/blob/master/docs/Operators.md

[4] github.com/egeersu/KnetONNX/tree/master/

[5] github.com/egeersu/KnetONNX/tree/master/

[6] github.com/egeersu/KnetONNX/tree/master/

[7] github.com/egeersu/KnetONNX/tree/master/

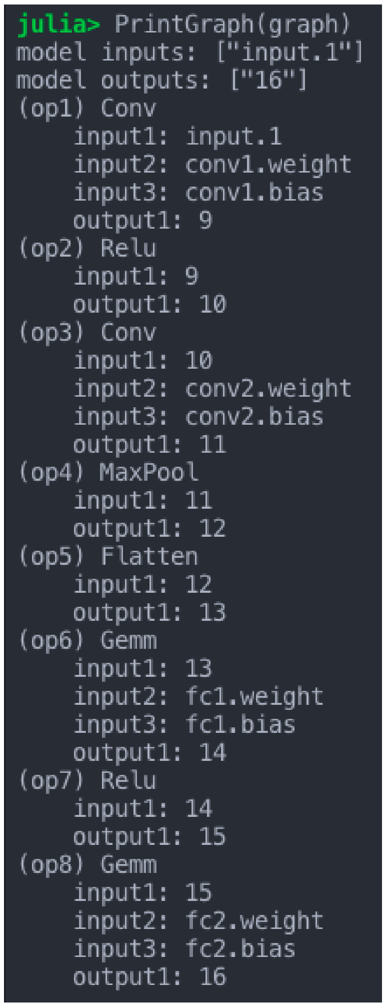
[8] github.com/egeersu/KnetONNX/tree/master/

[9] github.com/egeersu/KnetONNX/tree/master/

[10] github.com/egeersu/KnetONNX/tree/master/

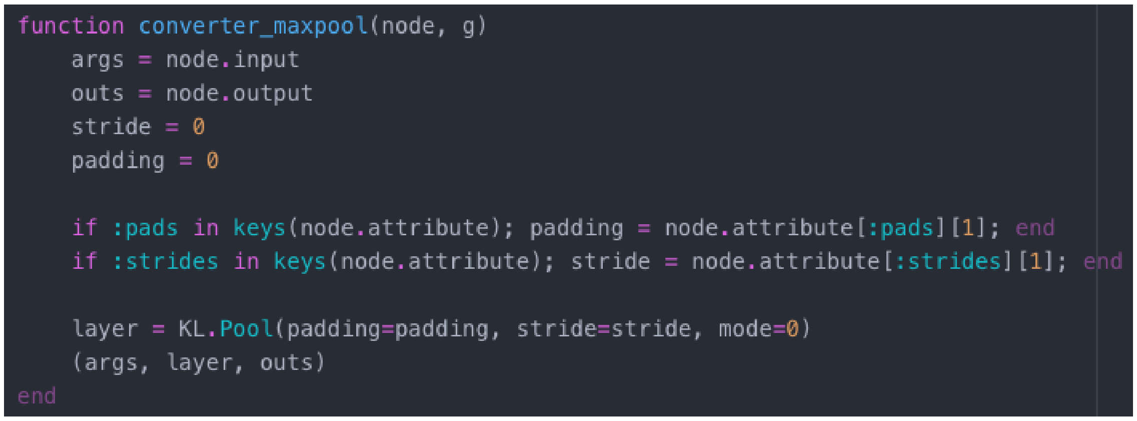
[11] github.com/onnx/models/tree/master/vision/classification/vgg

5 Appendix



```
julia> PrintGraph(graph)
model inputs: ["input.1"]
model outputs: ["16"]
(op1) Conv
    input1: input.1
    input2: conv1.weight
    input3: conv1.bias
    output1: 9
(op2) Relu
    input1: 9
    output1: 10
(op3) Conv
    input1: 10
    input2: conv2.weight
    input3: conv2.bias
    output1: 11
(op4) MaxPool
    input1: 11
    output1: 12
(op5) Flatten
    input1: 12
    output1: 13
(op6) Gemm
    input1: 13
    input2: fc1.weight
    input3: fc1.bias
    output1: 14
(op7) Relu
    input1: 14
    output1: 15
(op8) Gemm
    input1: 15
    input2: fc2.weight
    input3: fc2.bias
    output1: 16
```

Figure 2: An ONNX Graph in Julia



```julia
function converter_maxpool(node, g)
    args = node.input
    outs = node.output
    stride = 0
    padding = 0

    if :pads in keys(node.attribute); padding = node.attribute[:pads][1]; end
    if :strides in keys(node.attribute); stride = node.attribute[:strides][1]; end

    layer = KL.Pool(padding=padding, stride=stride, mode=0)
    (args, layer, outs)
end
```

Figure 3: A sample converter