



# Enhancing the Machine Learning Inference Engine

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#### **ROOT TMVA**





- Toolkit for Multivariate Analysis
- Provides a Machine Learning environment for training, testing and evaluation of multivariate methods.















System for





System for Optimized





System for Optimized Fast



System for Optimized Fast Inference



System for Optimized Fast Inference code Emit



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inference code, fast to operate, with least dependencies



#### Motivation



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- Inference in Tensorflow & PyTorch
  - supports only their own model
  - usage of C++ environment is difficult
  - heavy dependency
- Inference in ONNX (Open Neural Network Exchange)
  - can use ONNXRuntime by Microsoft
  - large dependency
  - difficult to integrate in HEP applications
    - control of libraries, threads
    - not optimized for single event evaluation





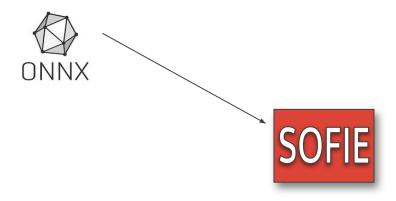
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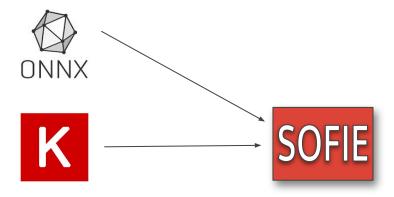


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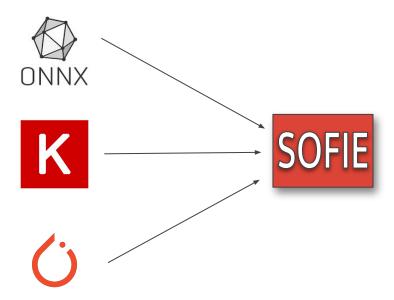


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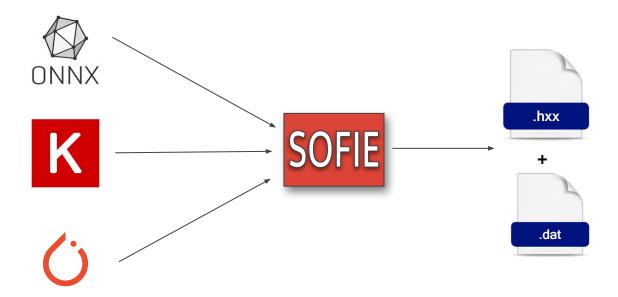


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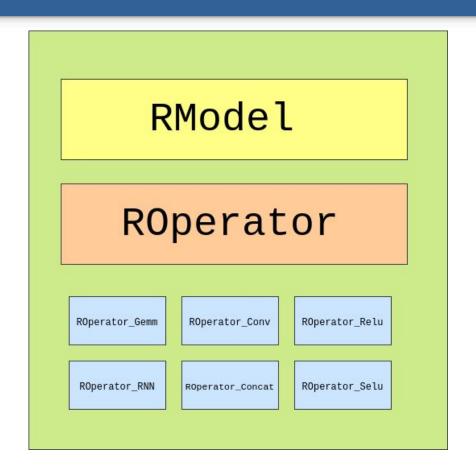




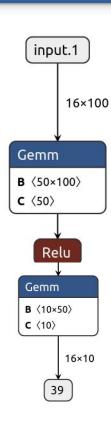
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Parser for translating an ONNX model to SOFIE's IR

```
using namespace TMVA::Experimental::SOFIE;
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Parser for translating Keras(.h5) models

SOFIE::RModel model = SOFIE::PyKeras::Parse("KerasModel.h5");
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Parser for translating Keras (.h5) models
     SOFIE::RModel model = SOFIE::PyKeras::Parse("KerasModel.h5");
Inference code generation
     // generate text code internally (with some options)
     model.Generate();
     // write output header file and data weight file
     model.OutputGenerated();
```



#### SOFIE's Generated code

```
namespace TMVA_SOFIE_Linear_event{
struct Session {
Session(std::string filename ="") {
 if (filename.empty()) filename = "Linear_event.dat";
 std::ifstream f;
 f.open(filename);
 ......
std::vector<float> infer(float* tensor_input1){
```





Extending support of SOFIE Keras parser



- Extending support of SOFIE Keras parser
- Implement SOFIE Custom operator support



- Extending support of SOFIE Keras parser
- Implement SOFIE Custom operator support
- Implement support for parsing Graph Neural Networks in SOFIE





No native support for ONNX translation



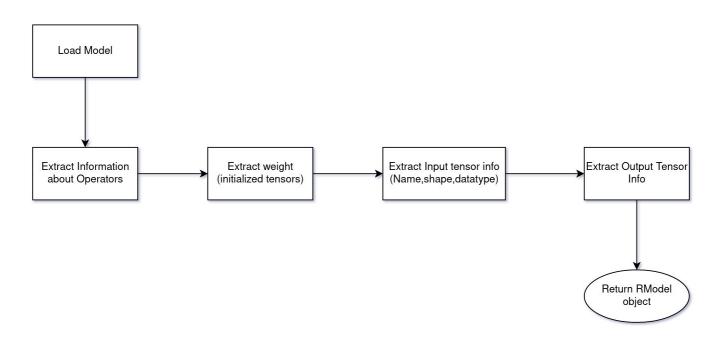
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- TF20NNX may convert a Keras .h5 model to ONNX
- SOFIE Keras Parser!
  - simpler to use
  - no need for input spec
  - built on latest opset



#### Algorithm for Parser





### **SOFIE Keras Parser**

#### **Current Support**

Keras Layer	Status
Dense	Implemented & Integrated
Permute	Implemented & Integrated
ReLU, Selu, Sigmoid	Implemented & Integrated
Batch Normalization	PR Merged
Convolution (2D)	PR Merged
Reshape	PR Merged
Basic Binary Operators: Add, Subtract, Multiply	PR Under Review
Activations: Softmax, LeakyRelu, Tanh	PR Drafted
Concat	PR Drafted





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- ONNX standards specifies 183 operators currently.
- Need a custom user operator specification
  - simple to define
  - easy to test, debug, and evaluate
  - few overheads and dependencies





- Define custom operator with the required attributes
  - Operator name
  - Input tensor names
  - Output tensor names
  - Output tensor shapes
  - Header file name



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#### **Current Plans & Implementation**

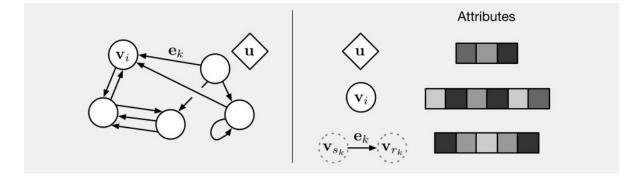
Following the DeepMind's Graph Nets architecture



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- Intermediate Representation
  - Nodes list
  - Edges list
  - Sender's list
  - o Receiver's list
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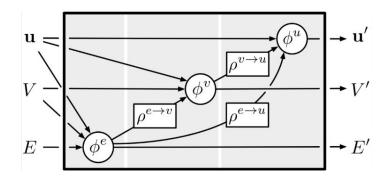


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#### Current plans for implementation

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- Operating functions
  - Updation functions
  - Aggregation functions





# **Future Plan**



#### **Future Plan**

• Finishing implementation & integration of Graph Neural Network support in SOFIE



#### **Future Plan**

- Finishing implementation & integration of Graph Neural Network support in SOFIE
- Implementing support for new operators in TMVA SOFIE



#### **Conclusion**

- Link to Forked Repository github.com/sanjibansg/root
- Link to SOFIE in current ROOT master github.com/root-project/root/tree/master/tmva/sofie
- Link to TMVA/SOFIE tutorials root.cern.ch/doc/master/group\_\_tutorial\_\_tmva.html
- Link to SOFIE notebooks github.com/lmoneta/tmva-tutorial/tree/master/sofie

#### Using SOFIE's Generated code

```
• • •
#include "Model.hxx"
TMVA_SOFIE_Model::Session s();
```



#### Using SOFIE's Generated code

```
import ROOT
ROOT.gInterpreter.Declare('#include "Model.hxx"')
s = ROOT.TMVA_SOFIE_Model.Session()
 result = s.infer(input)
```



#### **Definition**

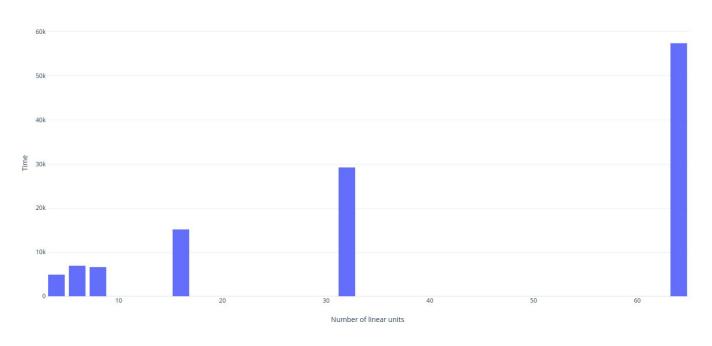
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#### Interface



#### **SOFIE Keras Parser**

#### Benchmarking for Keras





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#### Benchmarking for SOFIE

