Scikit Model inference in C++

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Outline

- Using models trained using scikit-learn in a C++ Application
  - Available options
    - ONNX
    - Treelite
    - PMML
    - ...
- Demo

Available Options

- Use an intermediate format
  - Model persistence options in scikit-learn.
    - ONNX
    - PMML
- ONNX
  - Use ONNX Runtime for inference
  - Focus of this presentation
- PMML
  - Use cPMML library for inference
  - Not being actively developed

Other Options

- Convert the model into a library.
  - treelite
    - Converts Tree based models to shared library.
    - Works only with tree based algorithms
  - Hummingbird
    - Compiles trained traditional ML models into tensor computations.
    - Works with tree based algorithms
- Use the same underlying library that scikit learn uses
  - liblinear or libsvm
    - No direct mapping available
    - Works only with logistic regression and SVM
- Call python interpreter from C++
  - Use libraries like pybind11, swig etc.
    - Possible loss of performance in conversion between data types of C++ and Python

ONNX

- Stands for **Open Neural Network Exchange**
- Definition from the official ONNX website
  - ONNX is an open format built to represent machine learning models.
  - ONNX defines a common set of operators - the building blocks of machine learning and deep learning models.
  - ONNX also defines a common file format to enable AI developers to use models with a variety of frameworks, tools, runtimes, and compilers.

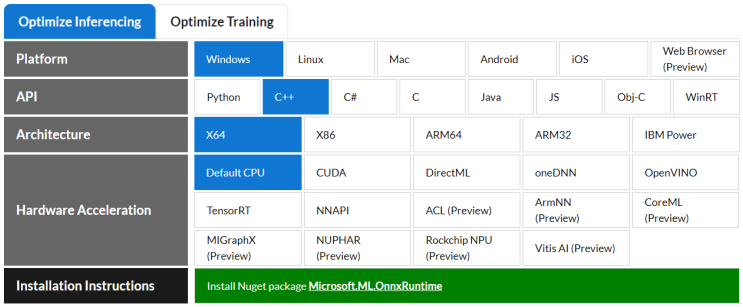
ONNX

```cpp
// Initialize
Ort::Env env;

// Load Model
auto session = Ort::Session(env, model_path, Ort::SessionOptions{ nullptr });

// Set inputs
Ort::MemoryInfo info("Cpu", OrtDeviceAllocator, 0, OrtMemTypeDefault);
auto input_tensor = Ort::Value::CreateTensor<float>(info,
                                                    const_cast<float*>(input.data()),
                                                    input.size(),
                                                    _input_shape.data(),
                                                    _input_shape.size());

// Inference
std::vector<Ort::Value> ort_outputs = _session.Run(Ort::RunOptions{ nullptr },
                                                   _input_names.data(),
                                                   &input_tensor, 1,
                                                   _output_names.data(), 2);

// Get outputs
auto type_info = ort_outputs[0].GetTensorTypeAndShapeInfo();
auto data_length = ort_outputs[0].GetStringTensorDataLength();
std::string result(data_length, '\0');
std::vector<size_t> offsets(type_info.GetElementCount());
ort_outputs[0].GetStringTensorContent((void*)result.data(), data_length, offsets.data(),
offsets.size());
```

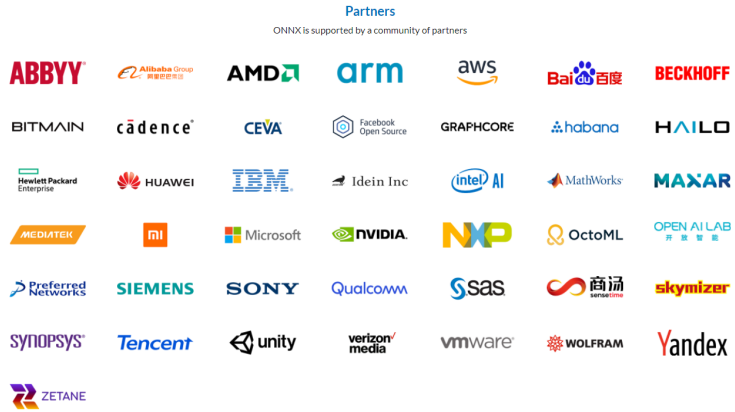
Figure 1: ONNX Inference code

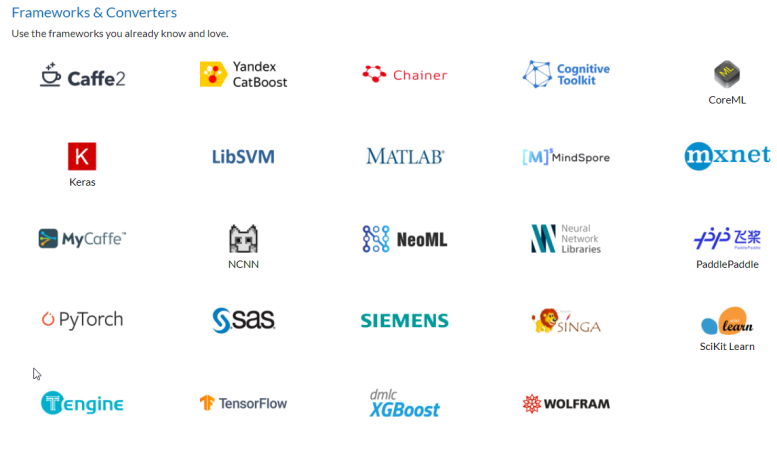
Why ONNX

- Open source.
- Community project backed by top companies
- Works with models of a wide range of frameworks.
- Works on a variety of platforms



Optimize Inferencing	Optimize Training					
Platform	Windows	Linux	Mac	Android	iOS	Web Browser (Preview)
API	Python	C++	C#	C	Java	JS	Obj-C	WinRT
Architecture	X64	X86	ARM64	ARM32	IBM Power	
Hardware Acceleration	Default CPU	CUDA	DirectML	oneDNN	OpenVINO	
	TensorRT	NNAPI	ACL (Preview)	ArmNN (Preview)	CoreML (Preview)	
	MIGraphX (Preview)	NUPHAR (Preview)	Rockchip NPU (Preview)	Vitis AI (Preview)		
Installation Instructions	Install Nuget package Microsoft.ML.OnnxRuntime					





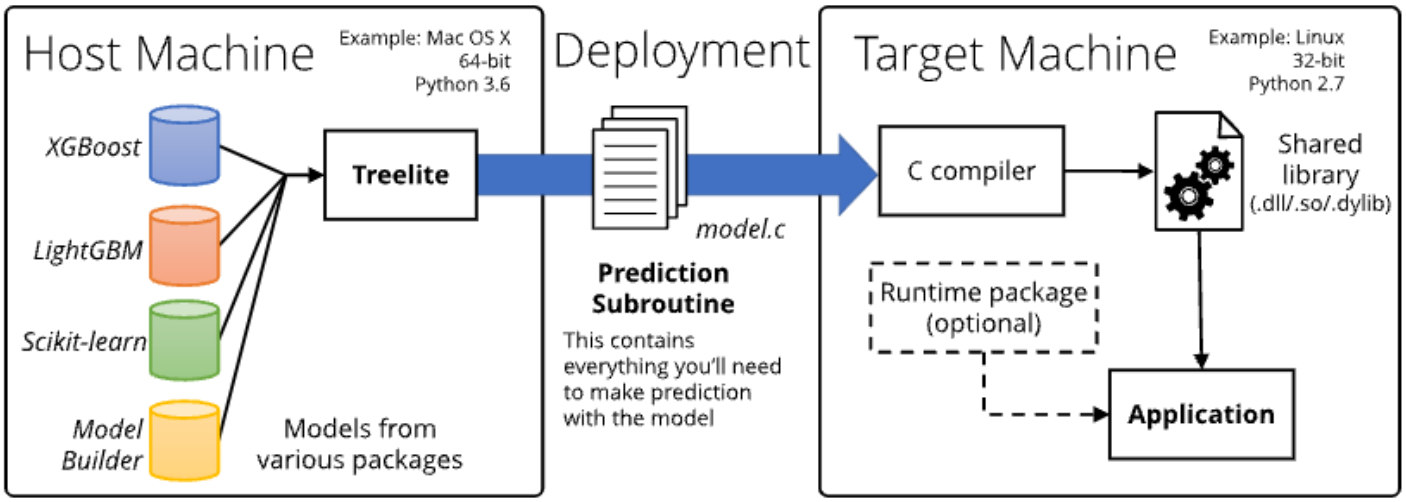
PMML

- Stands for Predictive Model Markup Language.
- XML based predictive model interchange format.

```
<?xml version="1.0" encoding="UTF-8" standalone="yes"?>
<PMML xmlns="http://www.dmg.org/PMML-4_4" xmlns:data="http://jpmml.org/jpmml-model/InlineTable" version="4.4">
    <Header>
        <Application name="JPMML-SkLearn" version="1.6.31"/>
        <Timestamp>2021-10-24T03:30:59Z</Timestamp>
    </Header>
    <MiningBuildTask>
        <Extension name="repr">PMMLPipeline(steps=[('classifier', RandomForestClassifier(n_estimators=20, random_state=0))])
</Extension>
    </MiningBuildTask>
    <DataDictionary>
    </DataDictionary>
    <MiningModel functionName="classification" algorithmName="sklearn.ensemble._forest.RandomForestClassifier">
        <MiningSchema>
        </MiningSchema>
        <Output>
            <OutputField name="probability(0)" optype="continuous" dataType="double" feature="probability" value="0"/>
            <OutputField name="probability(1)" optype="continuous" dataType="double" feature="probability" value="1"/>
            <OutputField name="probability(2)" optype="continuous" dataType="double" feature="probability" value="2"/>
            <OutputField name="probability(3)" optype="continuous" dataType="double" feature="probability" value="3"/>
            <OutputField name="probability(4)" optype="continuous" dataType="double" feature="probability" value="4"/>
            <OutputField name="probability(5)" optype="continuous" dataType="double" feature="probability" value="5"/>
            <OutputField name="probability(6)" optype="continuous" dataType="double" feature="probability" value="6"/>
            <OutputField name="probability(7)" optype="continuous" dataType="double" feature="probability" value="7"/>
            <OutputField name="probability(8)" optype="continuous" dataType="double" feature="probability" value="8"/>
            <OutputField name="probability(9)" optype="continuous" dataType="double" feature="probability" value="9"/>
        </Output>
        <LocalTransformations>
        </LocalTransformations>
        <Segmentation multipleModelMethod="average">
        </Segmentation>
    </MiningModel>
</PMML>
```

Treelite

- Definition from the website
  - Treelite is a model compiler for decision tree ensembles, aimed at efficient deployment.
  - Treelite overview



Treelite Example

```python
import sklearn.datasets
import sklearn.ensemble
import treelite.sklearn

X, y = sklearn.datasets.load_boston(return_X_y=True)
clf = sklearn.ensemble.RandomForestRegressor(n_estimators=10)
clf.fit(X, y)

treelite_model = treelite.sklearn.import_model_with_model_builder(clf)
treelite_model.export_lib(
    toolchain="gcc",
    libpath=str(lib_path),
    params={"parallel_comp": 8},
    verbose=True,
)
```

Figure 2: Treelite code

Hummingbird

- Hummingbird is a library for compiling trained traditional ML models into tensor computations
- Benefits
  - Leverage optimizations implemented in neural network frameworks
  - Gives native hardware acceleration
  - Both traditional and neural network models use same framework
- Support conversion of sklearn models to Pytorch, ONNX and TVM.

Hummingbird example

```python
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from hummingbird.ml import convert, load

# Create some random data for binary classification
num_classes = 2
X = np.random.rand(100000, 28)
y = np.random.randint(num_classes, size=100000)

# Create and train a model (scikit-learn RandomForestClassifier in this case)
skl_model = RandomForestClassifier(n_estimators=10, max_depth=10)
skl_model.fit(X, y)

# Use Hummingbird to convert the model to PyTorch
model = convert(skl_model, 'pytorch')

# Save the model
model.save('hb_model')
```

Figure 3: Hummingbird code

Resources

- Demo code and slides: https://github.com/abhilb/pydata_2021
- ONNX Runtime: https://onnxruntime.ai/
- ONNX: https://onnx.ai/
- Treelite: https://treelite.readthedocs.io/en/latest/
- PMML Spec: http://dmg.org/pmml/v4-4-1/GeneralStructure.html
- sklearn2pmml: https://github.com/jpmml/sklearn2pmml
- Hummingbird: https://github.com/microsoft/hummingbird