Multi-target Compiler for the Deployment of Machine Learning Models

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Content

Introduction

Introduction: Building Machine Learning Models

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    - Use tools/languages for a rapid model building/prototyping (R, Python (libraries), Weka, Knime, SAS, SPSS, etc.)
    - Their main objective is to create the best possible model.

Introduction: Predictive Modeling Process

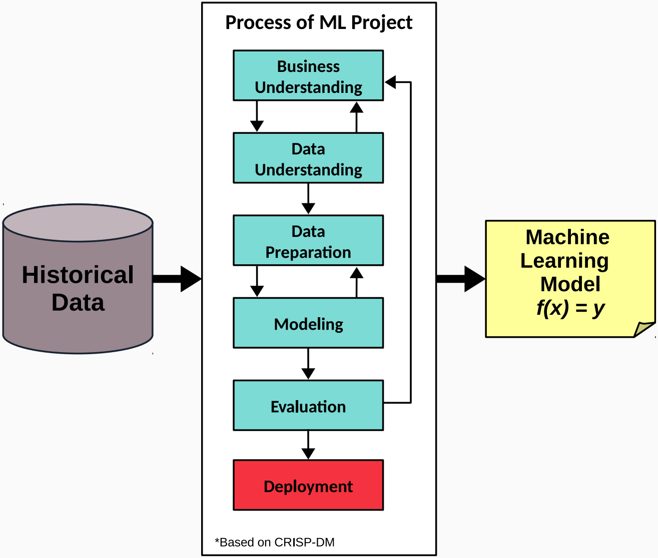

Figure 1: CRISP-DM Modeling Process

Introduction: Machine Learning Models in Production

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- In production it is where the model generates value through the predictions made on incoming data.
- The process of generating a prediction is also referred as *scoring* or *inference* (depending on the domain).

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General process of taking a model (math function) to a specific operating environment where it is available for its use (software).

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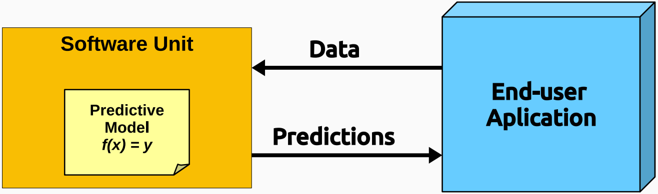

Figure 2: Predictive Model as a Software Unit

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- Deployment of ML models is a challenging task.
- Software in production is developed and maintained by Software Engineers who:
  - Are experts in software building tools: IDE's, SDK's, Frameworks, etc.
  - Aim to build software following requirements and quality attributes.

Introduction: Deployment issues and approaches

Model building vs Model deployment

- Both processes are done in different languages / environments

[1] Gartner 2019: Magic quadrant for data science and machine learning platforms and Gartner 2022: AI in Organizations

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Model building vs Model deployment

- Both processes are done in different languages / environments
- ML models integration must comply with Software design / architecture
- 60%(2019) and 53%(2022) of ML models are actually never deployed to production [1]

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- **Manual coding**, manually translate the model to a programming language.
- **IoT/Edge-Computing**, one-to-one compilation (commonly Deep learning models).

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- In-database and IoT-Edge are limited by specific cases.
- Manual coding is a labor-intensive task, prone to errors.

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Declarative $\rightarrow$ Procedural

Compiler

Compiler

We developed a multi-target compiler to translate Machine Learning models into source code to automate the deployment to production environments

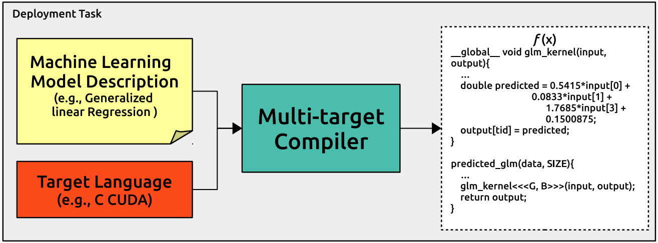

Figure 3: Multi-target compiler that translates ML models to source code

We can effectively automate the deployment task with a compiler

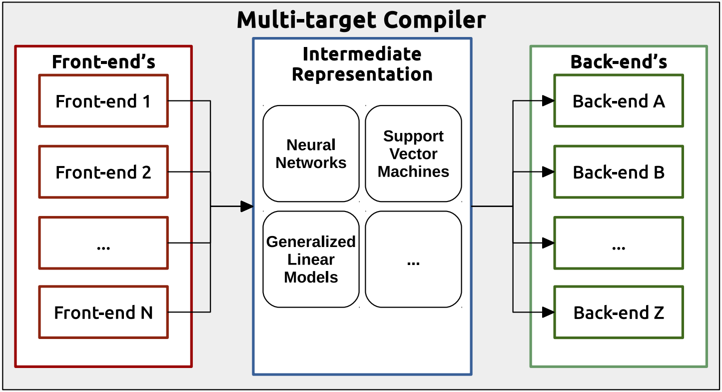

Figure 4: General design of the proposed multi-target compiler.

Intermediate Representation Template pt. 1

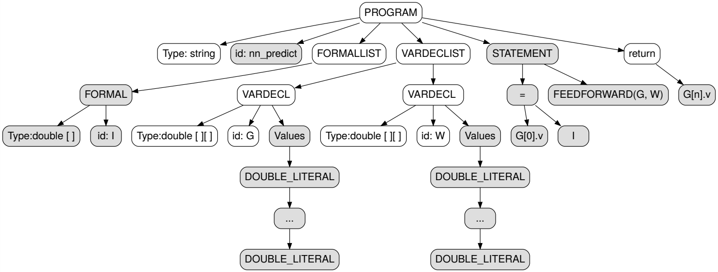

Figure 5: Example of a IR template for a neural network.

Intermediate Representation Template pt. 2

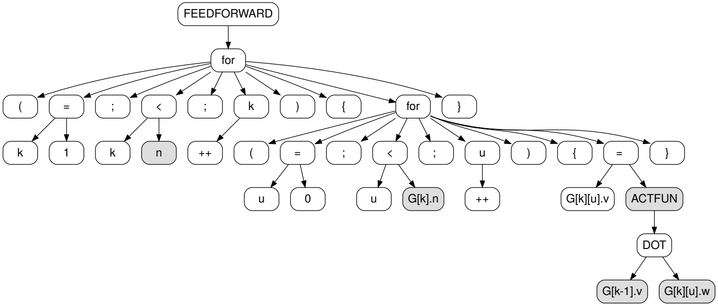

Figure 6: Example of feed forward computation of a neural network.

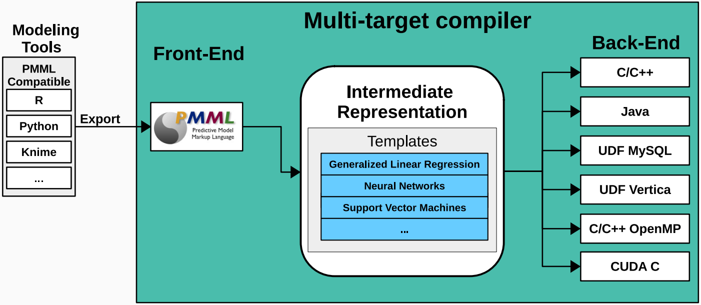

Figure 7: Implementation of the multi-target compiler.

Empirical evaluation

Validation and Evaluation

- The first validation is the correctness of the generated code. Predictions must be equal in the original model creation tool and generated code.

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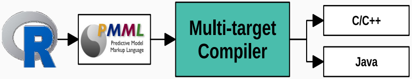
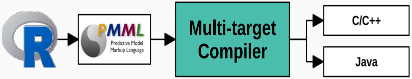
- Evaluation, testing the efficiency of the execution of the predictive models by using the generated code by the compiler.

Sequential experiments GLM models



Workflow

Sequential experiments GLM models



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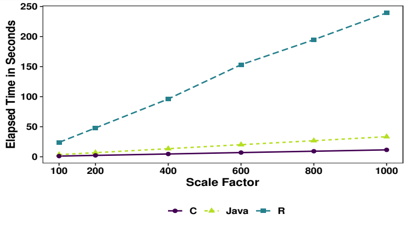
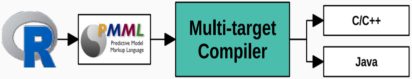


DCCC

Sequential experiments GLM models



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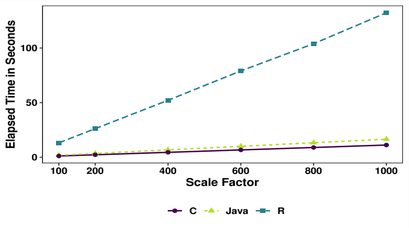
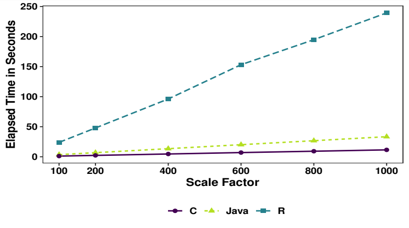


EGSS



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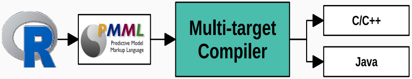

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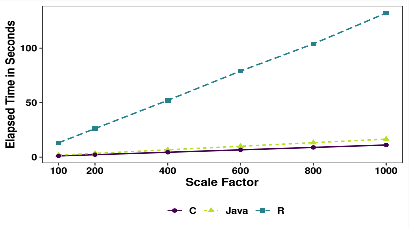

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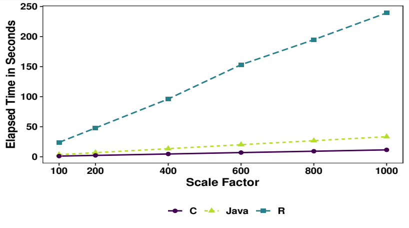

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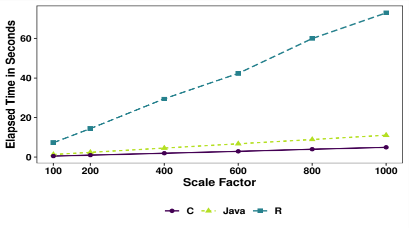
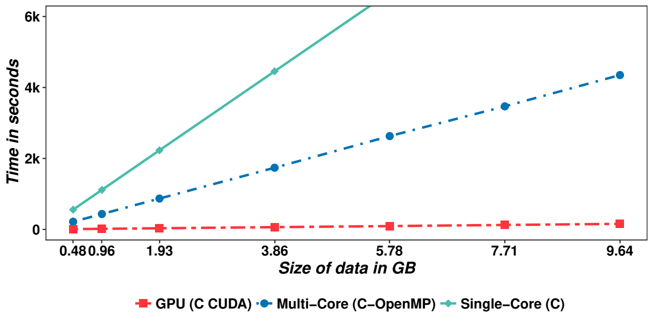


OSPI

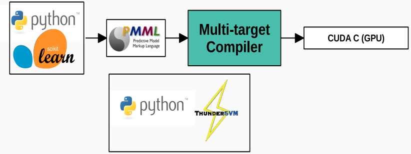
Sequential and parallel experiments with a SVM binary class model

Workflow



DCCC dataset

GPU Experiments with SVM multi-class model



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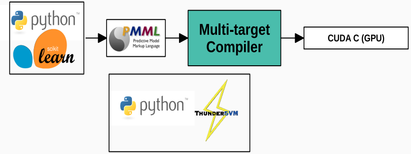

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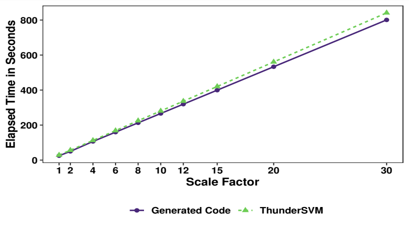

MNIST

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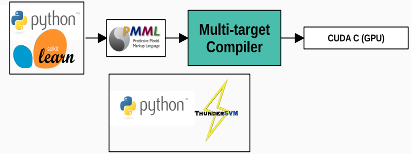

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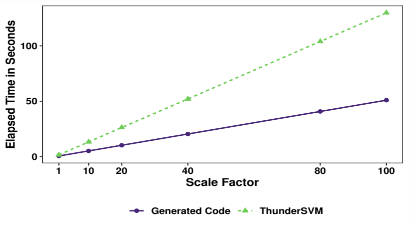
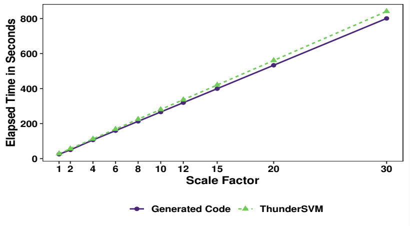


Poker



MNIST

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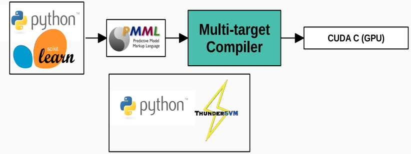

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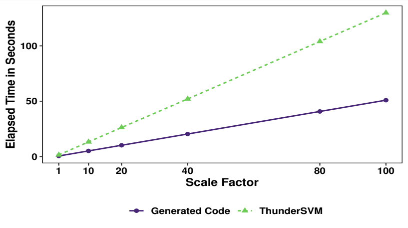
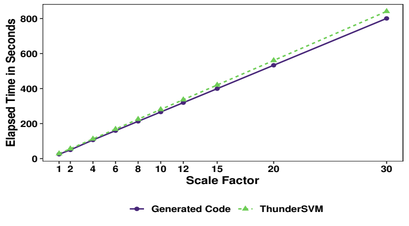
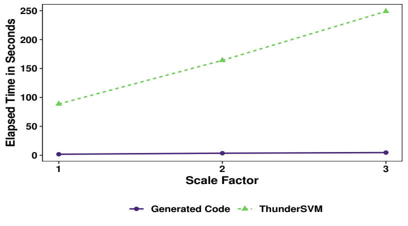


Poker



MNIST



RCV1

Conclusions

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- The code can be embedded inside operational environments (i.e. automate deployment) and is self-contained.
- We can effectively reduce the time-to-deploy.
- We can leverage sequential and parallel architectures for efficient scoring in production environments.
- The modularity in our compiler allows for an easy extension of both new types of models and new target languages.

References

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Current work/interests:

- **Speeding up programs.**
  - Special focus on Python.
  - Improving performance of DS/ML pipelines.
  - Code compilation/optimization.
  - Developing libraries: HPC, CUDA, Big Data.
- **Applied DS/ML.**

Thank you!!

Any questions?

Email: `oscar.castro@uni.lu`

Example of PMML

```xml
<PMML version="4.2">
 <Header copyright="Copyright (c) 2016 lcid" description="Neural Network PMML Model">
  <Extension name="user" value="lcid" extender="Rattle/PMML"/>
  <Application name="Rattle/PMML" version="1.4"/>
  <Timestamp>2016-12-09 18:56:44</Timestamp>
 </Header>
 <DataDictionary numberOfFields="9">
  <DataField name="MITBEAT_NN_FFT" optype="categorical" dataType="string">
   <Value value="A"/>
   <Value value="N"/>
  </DataField>
  <DataField name="V1" optype="continuous" dataType="double"/>
...
 </DataDictionary>
 <NeuralNetwork modelName="NeuralNet_model" functionName="classification" numberOfLayers="3"
      activationFunction="logistic">
...
   <OutputField name="Predicted_MITBEAT_NN_FFT" feature="predictedValue"/>
   <OutputField name="Probability_A" optype="continuous" dataType="double" feature="probability"
          value="A"/>
   <OutputField name="Probability_N" optype="continuous" dataType="double" feature="probability"
          value="N"/>
  </Output>
  <NeuralInputs numberOfInputs="8">
...
  </NeuralInputs>
  <NeuralLayer numberOfNeurons="28">
   <Neuron id="9" bias="0.83109384784387">
    <Con from="1" weight="-1.58888618835219"/>
...
   </Neuron>
...
   </Neuron>
  </NeuralLayer>
  <NeuralLayer numberOfNeurons="2" activationFunction="threshold" threshold="0.5">
   <Neuron id="38" bias="1.0">
    <Con from="37" weight="-1.0"/>
   </Neuron>
...
  </NeuralLayer>
  <NeuralOutputs numberOfOutputs="2">
   <NeuralOutput outputNeuron="38">
    <DerivedField name="derivedNO_MITBEAT_NN_FFT" optype="continuous" dataType="double">
     <NormDiscrete field="MITBEAT_NN_FFT" value="A"/>
    </DerivedField>
   </NeuralOutput>
   <NeuralOutput outputNeuron="39">
    <DerivedField name="derivedNO_MITBEAT_NN_FFT" optype="continuous" dataType="double">
     <NormDiscrete field="MITBEAT_NN_FFT" value="N"/>
    </DerivedField>
   </NeuralOutput>
  </NeuralOutputs>
 </NeuralNetwork>
</PMML>
```

Example of generated C code

```c
double *predicted_mitbeat_nn_fft(double in_v1, double in_v2, double in_v3, double in_v4, double
       in_v5, double in_v6, double in_v7, double in_v8){
        //Variable transformation
        double new_v1 = in_v1;
        ...
        // layer
        static double layer0[28];
        layer0[0] = 1*0.83109384784387+new_v1*-1.58888618835219+new_v2*-1.82672308266525+new_v3
              *3.33746196373367+new_v4*-0.386660430766735+new_v5*2.37454410956807+new_v6
              *-1.30898075446596+new_v7*-1.43872713454692+new_v8*2.4529341743543;
        layer0[0] = 1 / (1+exp(-layer0[0]));
        ...
        // layer
        static double layer1[1];
        layer1[0] = 1*-4.62592500800819+layer0[0]*-1.03197631554537+layer0[1]*6.43276062612687+
              layer0[2]*3.06106357914918+layer0[3]*4.25114324158677+layer0[4]*-1.81616145986666+
              layer0[5]*-2.64384641103975+layer0[6]*-1.5951340774553+layer0[7]*1.27863903623786+
              layer0[8]*0.707355744671864+layer0[9]*-1.76172788928607+layer0
              [10]*0.53212821423806+layer0[11]*-1.96944871187955+layer0[12]*-1.7584593904505 6+
              layer0[13]*-1.08114467050309+layer0[14]*1.75717862584521+layer0
              [15]*-0.364837336276863+layer0[16]*0.991809219615911+layer0
              [17]*-0.194322645909799+layer0[18]*-1.16222444790653+layer0[19]*-2.48554250501996+
              layer0[20]*-0.225800791983646+layer0[21]*-0.957736167039977+layer0
              [22]*-2.89636184187767+layer0[23]*5.69469441754116+layer0[24]*0.730216654347973+
              layer0[25]*-2.22926009625776+layer0[26]*-3.14190898011756+layer0
              [27]*2.20678305117676;
        layer1[0] = 1 / (1+exp(-layer1[0]));

        // layer
        static double layer2[2];
        layer2[0] = 1*1.0+layer1[0]*-1.0;
        layer2[0] = (layer2[0]>0.5)? 1.0 : 0.0;
        layer2[1] = 1*0.0+layer1[0]*1.0;
        layer2[1] = (layer2[1]>0.5)? 1.0 : 0.0;

        return layer2;
}
char const * predicted_mitbeat_nn_fft_response(double probabilities[]){
        char const *  labels[] = {"A", "N"};
        int max = 0;
        int i;
        for (i = 1; i < 2; i++) {
                if(probabilities[i]>probabilities[max])
                        max =i;
        }
        return labels[max];
}
```

Datasets

- DCCC. Default of Credit Card (Kaggle).
- EGSS. Electrical Grid Stability Simulated (UCI).
- OSGI. Online Shoppers' Purchasing Intention (UCI).
- MNIST. It is a database of images of handwritten digits (LIBSVM Data).
- Poker. This is the poker hand dataset (LIBSVM Data).
- RCV1. This is the Reuters Corpus Volume 1 dataset (LIBSVM Data).

- Kaggle: `https://www.kaggle.com/datasets`
- UCI: `https://archive.ics.uci.edu/ml/datasets.php`
- LIBSVM: `https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/multiclass.html`

Computer equipment

- Workstation Intel Xeon W-2133 CPU 6 cores 3.60 GHz, 64 GB RAM.
- GPU GeForce GTX 1080 8GB RAM, 2,560 CUDA cores.