ML-LLVM-Tools: Towards Seamless Integration of Machine Learning in Compiler Optimizations

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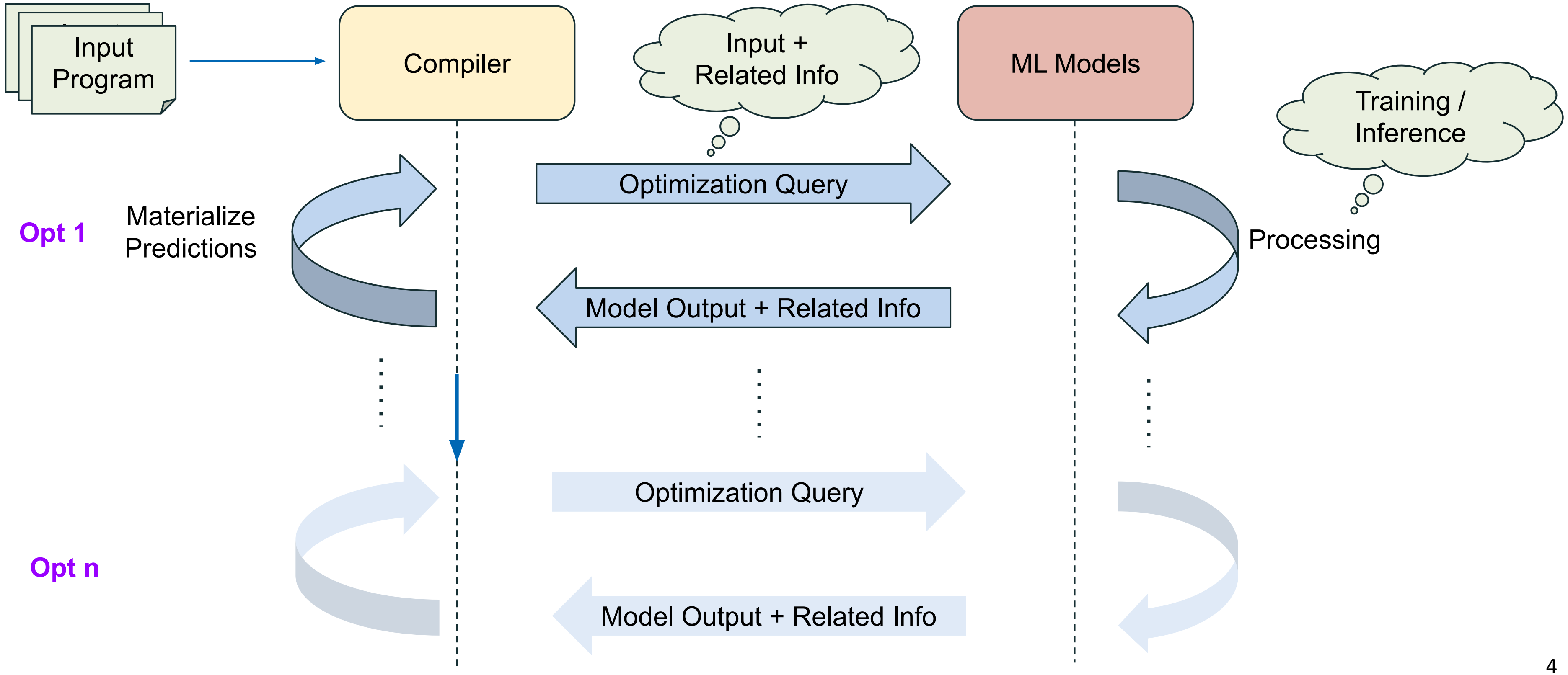
Overview

- ML in Compiler Optimizations
  - Scheme of ML in Compiler Optimizations
  - Proposed Infrastructure
- LLVM-gRPC: gRPC based framework to support Training
  - LLVM-gRPC Usage
  - Use Case: RL4ReAl, IR2Vec
- LLVM-InferenceEngine: ONNX based framework to support Inference
  - Proposed Inference Flow
  - LLVM-InferenceEngine Usage
  - Compile Time Comparison
- Related Works
- Summary

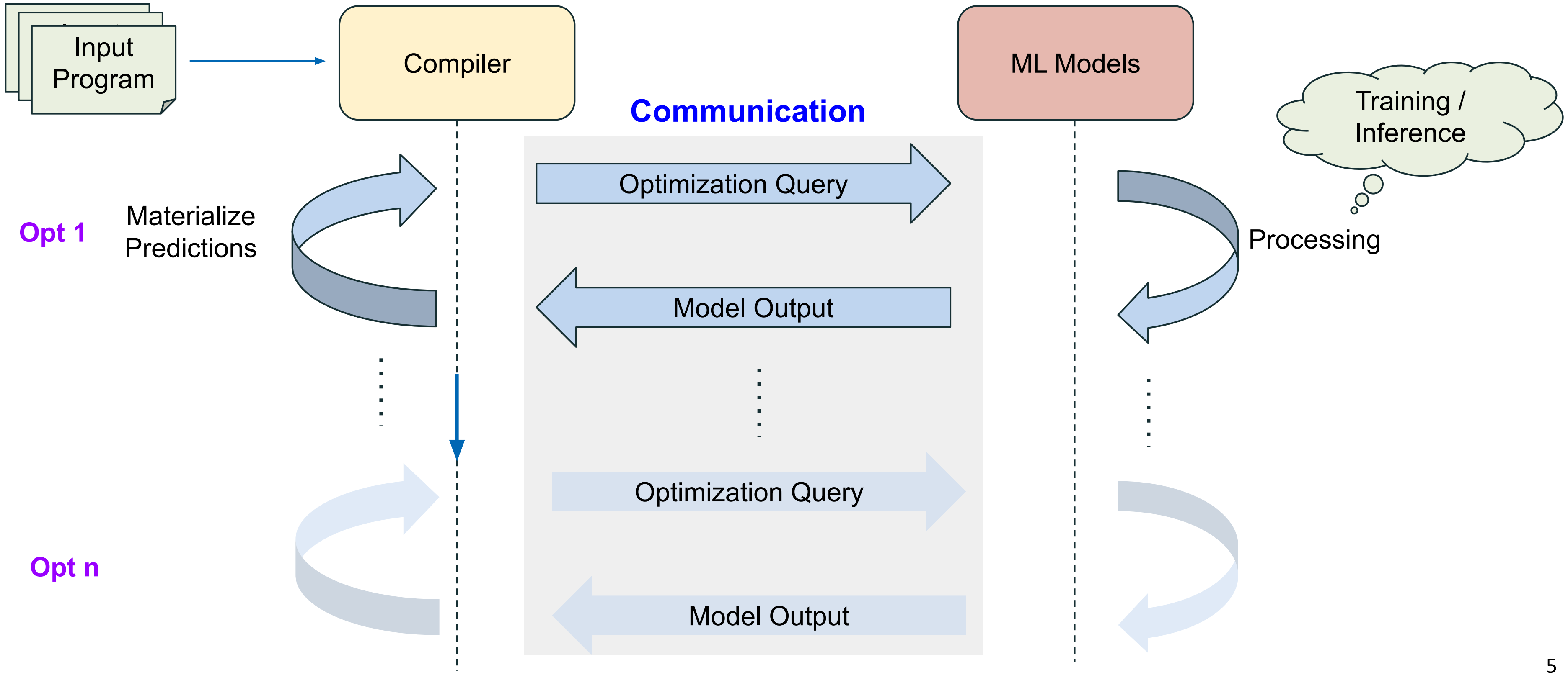
ML in Compiler Optimizations

- Impact of ML in *hard, heuristic-based* compiler optimizations
  - Success of ML in NLP, Image Processing, etc.
- Several ML based compiler optimizations exist
  - From late 90s to date
- ML based optimizations
  - Loop Vectorization, Loop Distribution, Function Inlining, Phase Ordering, Register Allocation, …
- ML in LLVM
  - Inlining decisions (From 11.x), Eviction in Register Allocation (From 14.x)

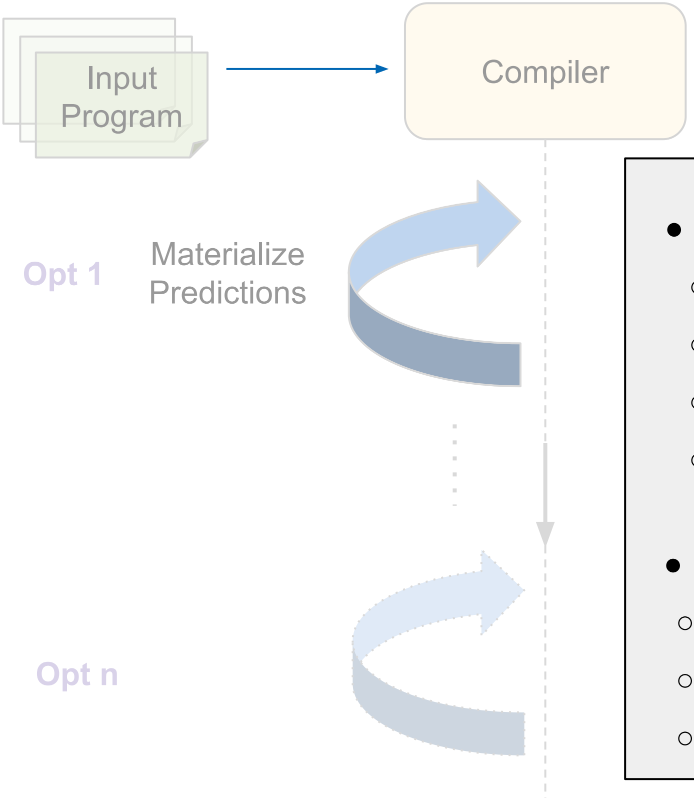
Scheme of ML in Compiler Optimizations



Scheme of ML in Compiler Optimizations

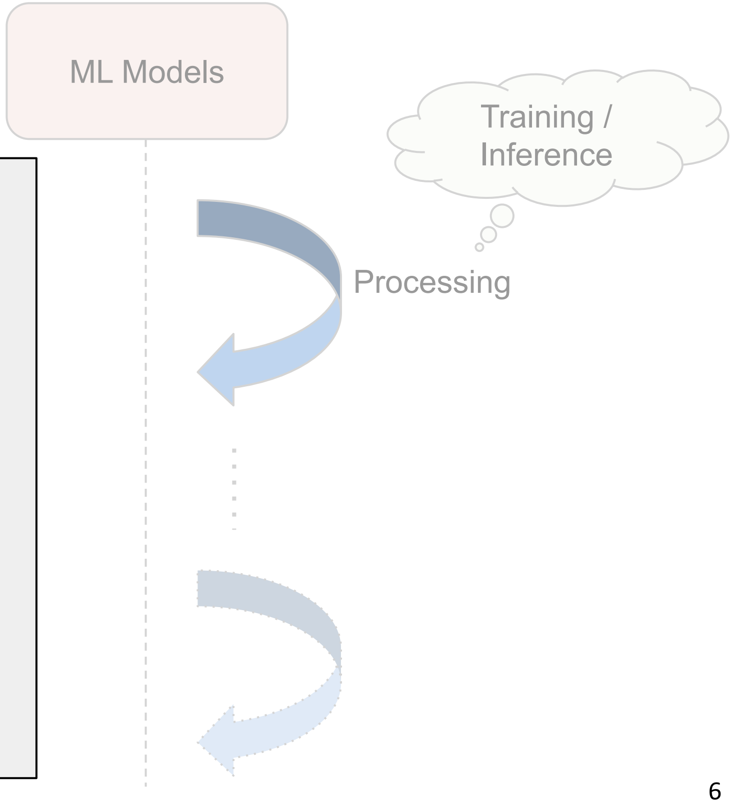


Focusing on Communication ...

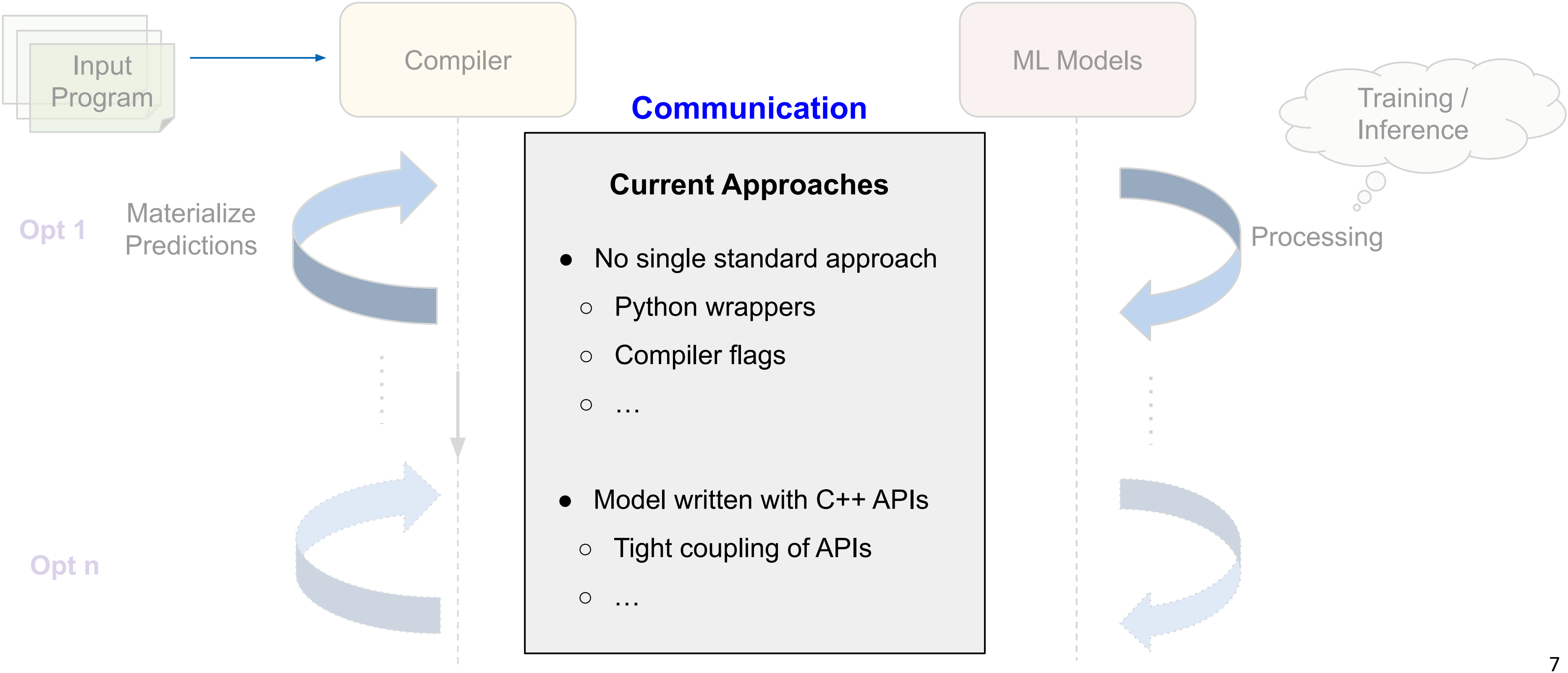


Communication

- **Highly Important**
  - Scalability
  - Compile Time Issues
  - Memory Issues
  - …
- **Determines the practicality**
  - Deployment
  - Usability
  - …



Focusing on Communication …



Current Approaches

- No single standard approach
  - Python wrappers
  - Compiler flags
  - …
- Model written with C++ APIs
  - Tight coupling of APIs
  - …

Limitations of Current Approaches

Scalability	Integratability	Programmability	Portability
• Python/C++ wrappers • 6x – 100x slowdown **Phase Ordering, Loop Distribution, …**	Not all outputs can be communicated via flags **Register Allocation, Instruction Scheduling, …**	Models written in C++ are not ML developer friendly **RLLib, SciPy, …**	Support for diverse ML frameworks **TF, PyTorch, JAX, …**

Need for **scalable**, **versatile** and **common** framework for ML-based optimizations in LLVM

Proposed Infrastructure

Framework + Architecture independent Infrastructure in LLVM

Training

- ML model development in any generic framework
- ML practitioners can develop solutions in Python

LLVM-gRPC

gRPC based library

Inference

- Within LLVM
- Trained models to be exported and linked with LLVM toolchain

LLVM-InferenceEngine

ONNX based library

LLVM-gRPC

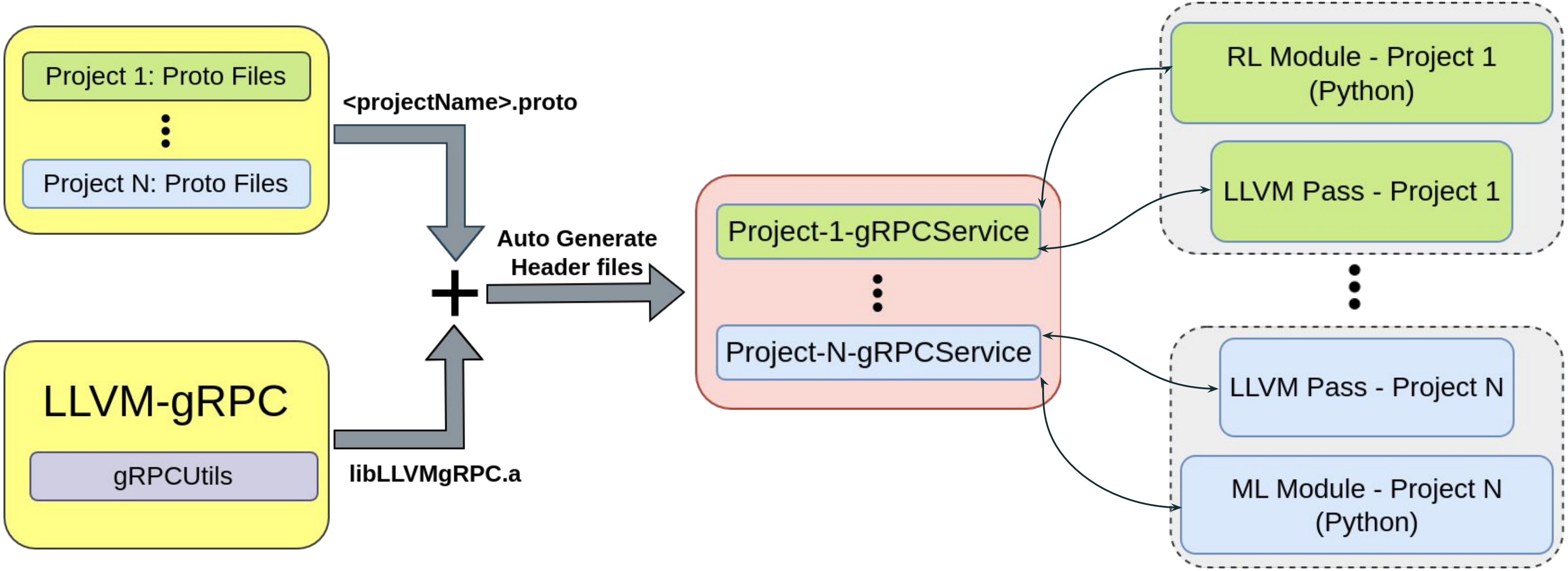
gRPC based framework to support Training

LLVM-gRPC

- Need for a seamless connection between LLVM and Python ML workloads
    - Interprocess communication
- gRPC: Modern open source high performance Remote Procedure Call
- LLVM-gRPC
    - Works as an LLVM library
    - Easy integration – As simple as implementing a few API calls
    - Support for any ML + RL workloads
- Use-case: RL4ReAl [CC'23]

S. VenkataKeerthy, Siddharth Jain, Anilava Kundu, Rohit Aggarwal, Albert Cohen, and Ramakrishna Upadrasta. RL4ReAl: Reinforcement Learning for Register Allocation. CC 2023. https://compilers.cse.iith.ac.in/publications/rl4real/

LLVM-gRPC + Passes



Example Proto File

```
syntax = "proto3";

package demopass;

// demo pass Service
service demoPass{
// RPC function to send and receive data
// between server and client
rpc getPassInfo(RequestData) returns (PassInfo) {}
}
```

demoPass: Defines the service (a C++ class) which will be auto generated

getPassInfo: Defines the RPC function which has to be overridden

```
message RequestData {
string functionName=1;
}

message PassInfo {
int32 numInstruction=1;
}
```

Datafields that will be auto generated using gRPC

Files generated on compiling proto file:

- demoPass.grpc.pb.cc
- demoPass.grpc.pb.h
- demoPass.pb.cc
- demoPass.pb.h
- demoPass_pb2_grpc.py
- demoPass_pb2.py

LLVM-gRPC Usage: C++ Server

```
using demopass::RequestData;
using demopass::PassInfo;
using grpc::Status;
using grpc::ServerContext;
using demopass::demoPass;
```

Types coming from demoPass.grpc.pb.h

```
struct Hello : public FunctionPass,demoPass::Service,gRPCUtil {
```

Inheriting classes

```
grpc::Status getPassInfo(grpc::ServerContext* context,
  const RequestData* request, PassInfo* response) override {
   // Pass logic to handle the request goes here
   ...
   return Status::OK;
}
```

Implementation of gRPC function

```
bool runOnFunction(Function &F) override {
   ...
   RunService(this,"0.0.0.0:50051");
   ...
   if(exit_requested) { free(exit_requested);}
   return false;
}
}
```

Blocking call to start the C++ server

Exiting blocking call

LLVM-gRPC Usage: Python Client

```
import grpc
import demoPass_pb2_grpc, demoPass_pb2
```

Service class defined in demoPass_pb2_grpc.py

```
class demoPassClient(demoPass_pb2_grpc.demoPassServicer):
```

Inheriting classes

```
  def __init__(self):
    self.host='localhost'
    self.server_port=50051
    self.channel=grpc.insecure_channel(
     '{}:{}'.format(self.host,self.server_port))
    self.stub= demoPass_pb2_grpc.demoPassStub(self.channel)
```

Creating a channel and stub from existing service

```
  def getRequest(self,requestData):
    request=demoPass_pb2.RequestData(requestData)
    return  (self.stub.getPassInfo(request))
```

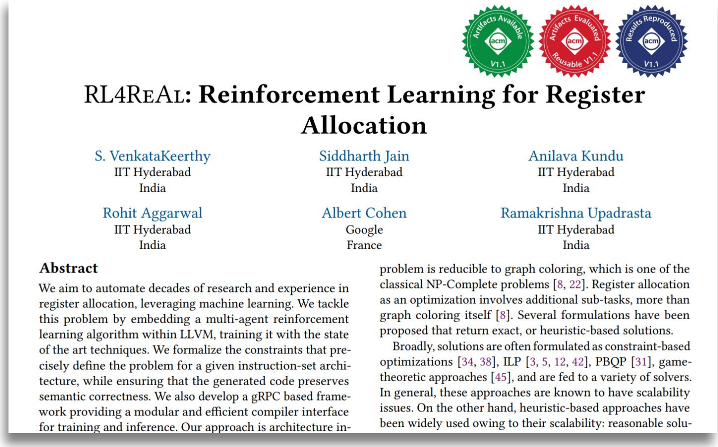
Call to gRPC function

```
if __name__ == '__main__':
  client=demoPassClient()
  functionName=demoPass_pb2.functionName(self.current_fuction_name)
  instruction_count=client.getPassInfo(functionName)
```

Use Case: RL4ReAl

RL4ReAl: Reinforcement Learning for Register Allocation

- RL based register allocator for LLVM compiler
- Models regalloc as graph coloring problem
- Based on MIR2Vec for Machine IR
    - An Extension of IR2Vec
- Uses LLVM-gRPC



RL4REAL: **Reinforcement Learning for Register Allocation**

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Abstract

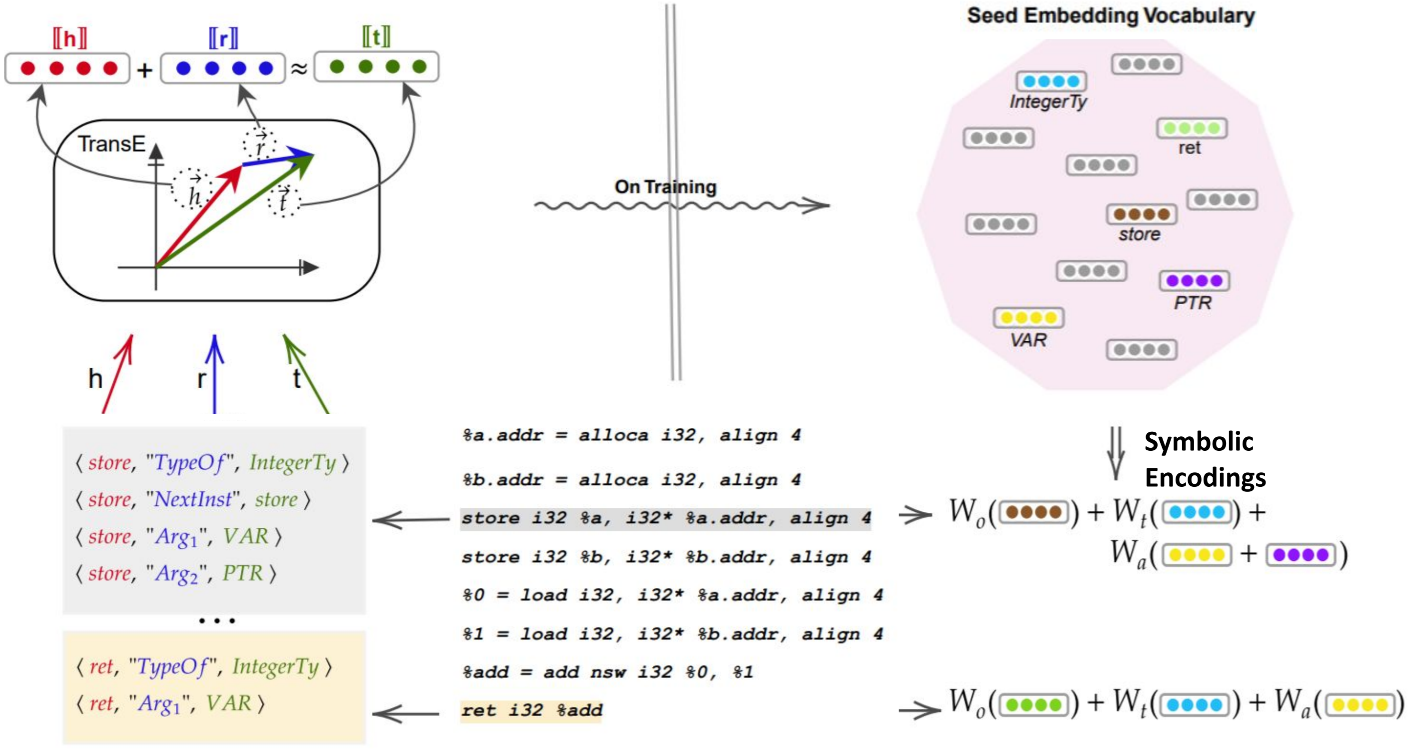
We aim to automate decades of research and experience in register allocation, leveraging machine learning. We tackle this problem by embedding a multi-agent reinforcement learning algorithm within LLVM, training it with the state of the art techniques. We formalize the constraints that precisely define the problem for a given instruction-set architecture, while ensuring that the generated code preserves semantic correctness. We also develop a gRPC based framework providing a modular and efficient compiler interface for training and inference. Our approach is architecture in-

problem is reducible to graph coloring, which is one of the classical NP-Complete problems [8, 22]. Register allocation as an optimization involves additional sub-tasks, more than graph coloring itself [8]. Several formulations have been proposed that return exact, or heuristic-based solutions.

Broadly, solutions are often formulated as constraint-based optimizations [34, 38], ILP [3, 5, 12, 42], PBQP [31], game-theoretic approaches [45], and are fed to a variety of solvers. In general, these approaches are known to have scalability issues. On the other hand, heuristic-based approaches have been widely used owing to their scalability: reasonable solu-

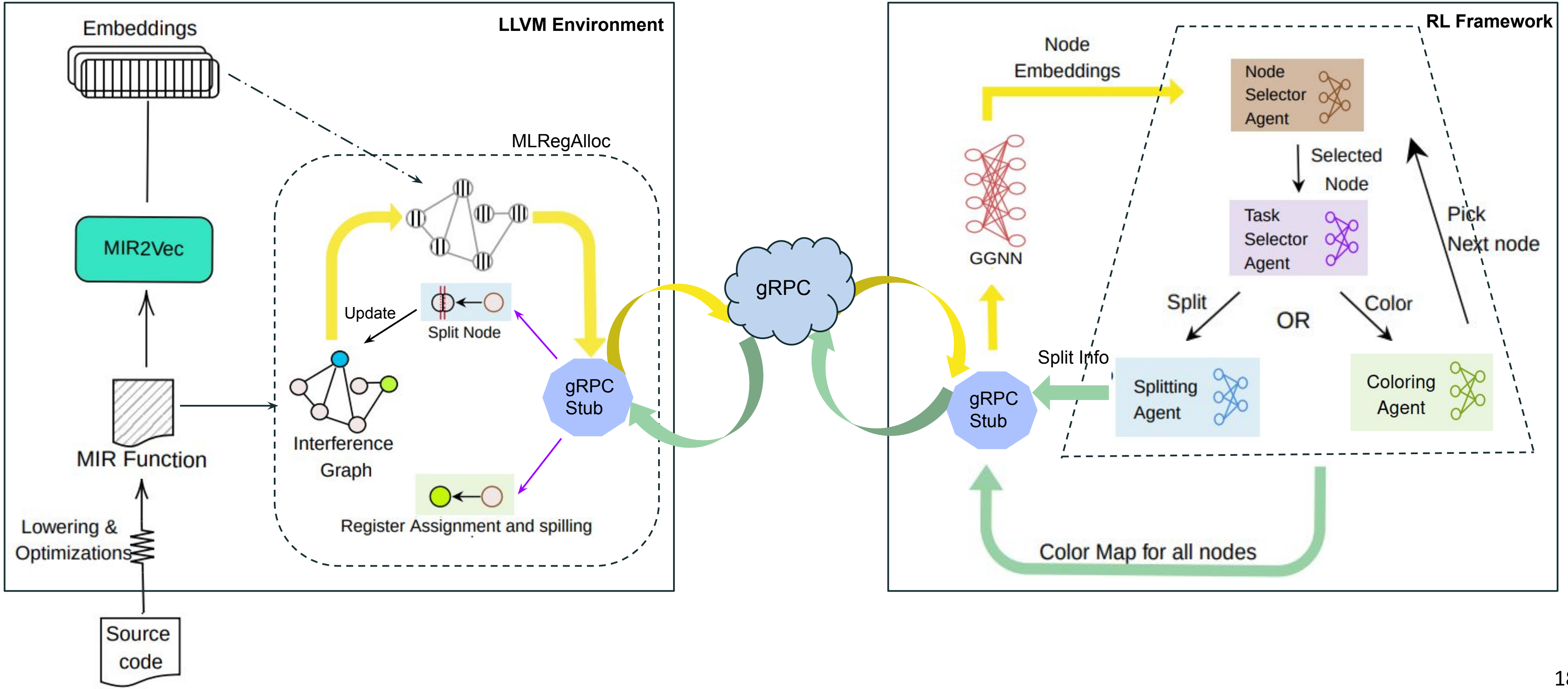
S. VenkataKeerthy, Siddharth Jain, Anilava Kundu, Rohit Aggarwal, Albert Cohen, and Ramakrishna Upadrasta. RL4ReAl: Reinforcement Learning for Register Allocation. CC 2023. https://compilers.cse.iith.ac.in/publications/rl4real/

IR2Vec: LLVM IR Based Scalable Program Embeddings



S. VenkataKeerthy, Rohit Aggarwal, Shalini Jain, Maunendra Sankar Desarkar, Ramakrishna Upadrasta, and Y. N. Srikant. IR2VEC: LLVM IR Based Scalable Program Embeddings. ACM TACO. 2020. https://compilers.cse.iith.ac.in/projects/ir2vec/

RL4ReAl: Reinforcement Learning for Register Allocation



Pros + Cons ...

Ease of development

- Transparent to DL/RL algorithms/policies
- Supports diverse ML/DL frameworks

Ease of training

- Multiple GPUs distributed training
- Parallel workers for sample collection

Reusability of code

Write specifications once and use in both Python and C++

However, LLVM-gRPC is insufficient for inference -

- Overhead on compile time
  - Interprocess communication
- Not transparent to user (application developer)

LLVM-InferenceEngine

ONNX based framework to support Inference

LLVM-InferenceEngine

- Framework neutral, interoperable infrastructure for trained model integration
- ONNX: Open Neural Network Exchange
  - Linux Foundation Project (LF AI & Data)
  - Operates in most of the native languages
  - Supported by all major ML/DL frameworks
- Usecase study - RL4ReAl [CC'23], POSET-RL [ISPASS'22]

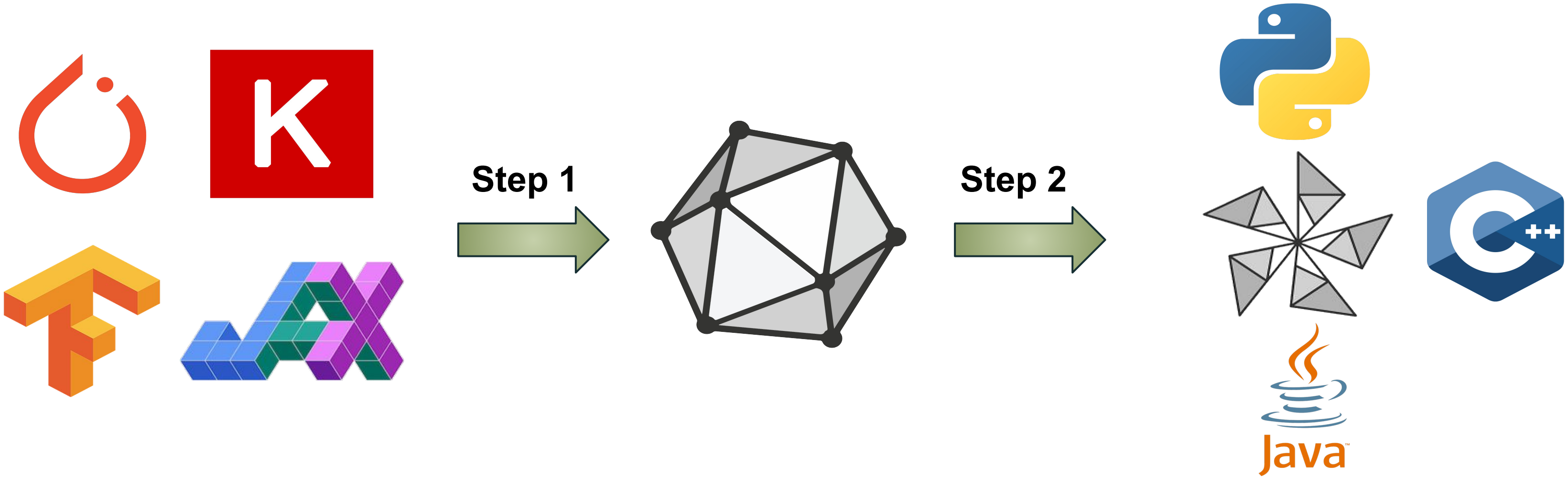
ONNX

ONNX. Open Neural Network Exchange. 2017, https://github.com/onnx/onnx

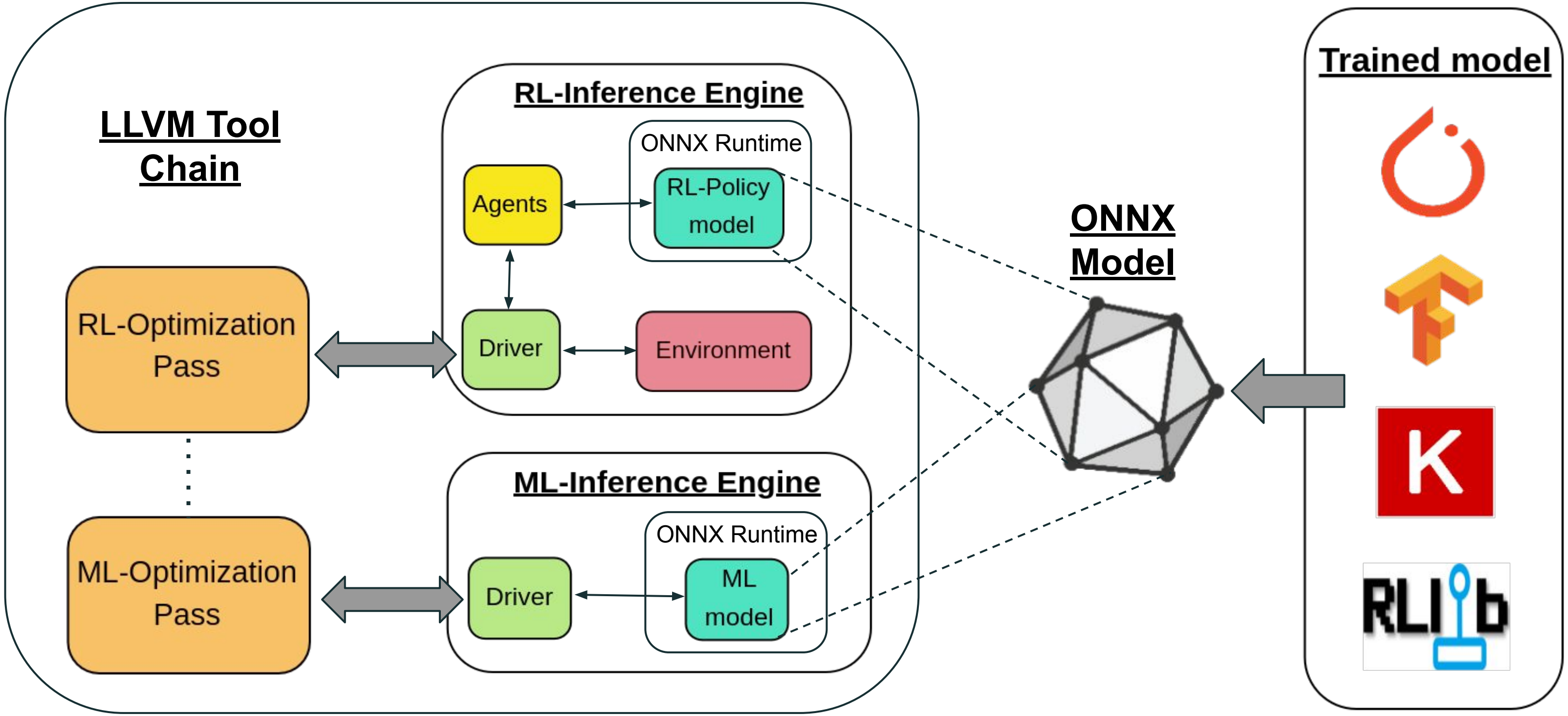
Shalini Jain, Yashas Andaluri, S. VenkataKeerthy and Ramakrishna Upadrasta. POSET-RL: Phase ordering for Optimizing Size and Execution Time using Reinforcement Learning. ISPASS 2022. https://compilers.cse.iith.ac.in/projects/posetrl/

Model Integration

- **Step 1:** Exporting trained model from native to ONNX format
- **Step 2:** Importing model in compiler with ONNX (C++) runtime environment



Proposed Inference Flow



LLVM-InferenceEngine Usage

```
#include "environment.h"
#include "inference-engine.h"

struct Hello : public FunctionPass, Environment {

bool runOnFunction(Function &F) override {
  ...

 InferenceEngine* inference_driver =
     new InferenceEngine(Environment* env);
 inference_driver->getPassInfo(PassData passData,
     OptInfo &predictions);

  ...
}
```

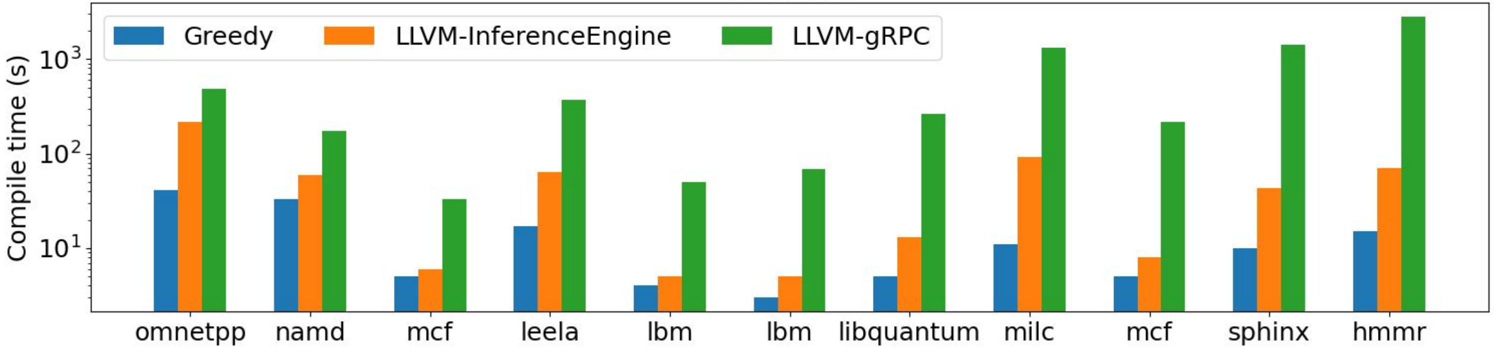
Inheriting Environment class

InferenceEngine: Creates instance of class InferenceEngine class

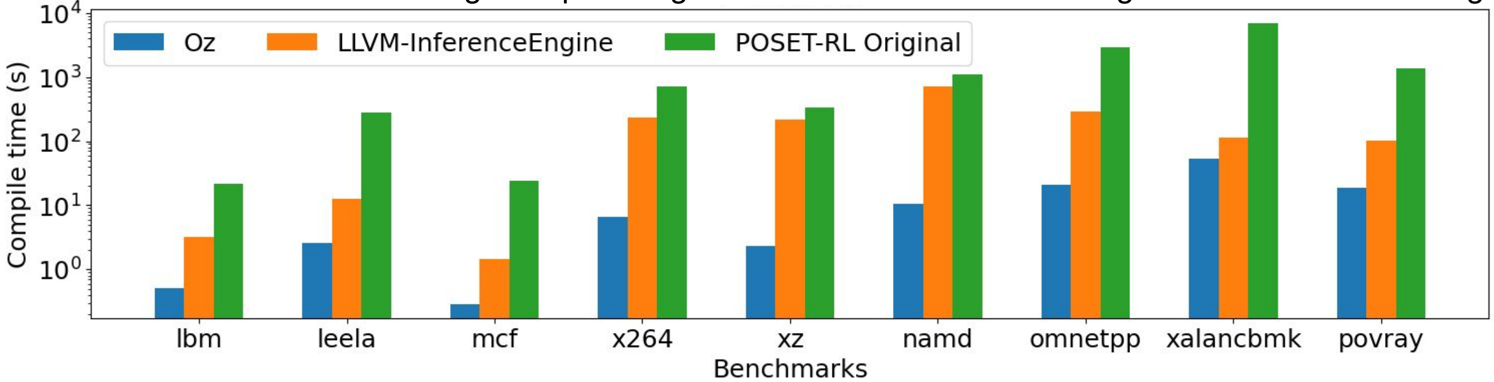
getPassInfo: Function to compute predictions from model

Compile Time Comparison

RL4ReAl: Reinforcement Learning for Register Allocation



POSET-RL: Phase ordering for Optimizing Size and Execution Time using Reinforcement Learning



Advantages

Features/Advantages of LLVM-InferenceEngine

In-process communication

- No RPC calls, IO, etc.

Lesser compilation time overhead

- No communication overhead

Versatile + Common infrastructure

- Framework and model agnostic

Transparent to the user/programmer

Other Related Works

- MLGO: A Machine Learning Framework for Compiler Optimization
    - Integrated with LLVM
    - Uses TensorFlow APIs and/or raw inter-process communication
    - We would like to explore different scenarios and use cases
        - RL Vs. ML, …; Single Vs. Multiple communication
- CompilerGym
    - Provides environments for training RL based compiler optimizations

Mircea Trofin, et al. "MLGO: a machine learning guided compiler optimizations framework." arXiv preprint 2021. https://arxiv.org/abs/2101.04808

Chris Cummins, et al. "CompilerGym: Robust, Performant Compiler Optimization Environments for AI Research." CGO 2022. https://github.com/facebookresearch/CompilerGym

Summary

- Scalable, Versatile and Common framework for ML-based optimizations in LLVM
  - Framework + Architecture independent Infrastructure
- Two components
  - Training - LLVM-gRPC
  - Inference - LLVM-InferenceEngine
- gRPC based training within Python in a framework independent manner
- In-memory ONNX based library for inference in a transparent manner
- Infrastructure is lightweight showing promising trends
- https://compilers.cse.iith.ac.in/publications/ml-llvm-tools

Thank you!

https://compilers.cse.iith.ac.in/publications/ml-llvm-tools