Accelerate AI Inference

2024 | Updates are here.
Post your questions here.
Read the documentation here.

Overview Cheat Sheet

Bring AI everywhere with OpenVINO™: enabling developers to quickly optimize, deploy, and scale AI applications across hardware device types with cutting-edge compression features and advanced performance capabilities.

What is OpenVINO™?

OpenVINO is an open-source toolkit for optimizing and deploying deep learning models. Deploy AI across devices (from PC to cloud) with automatic acceleration!

Documentation | Get started | Blog | Examples

Use OpenVINO with...

PyTorch | TensorFlow | Hugging Face | ONNX | and more

Build, Optimize, Deploy

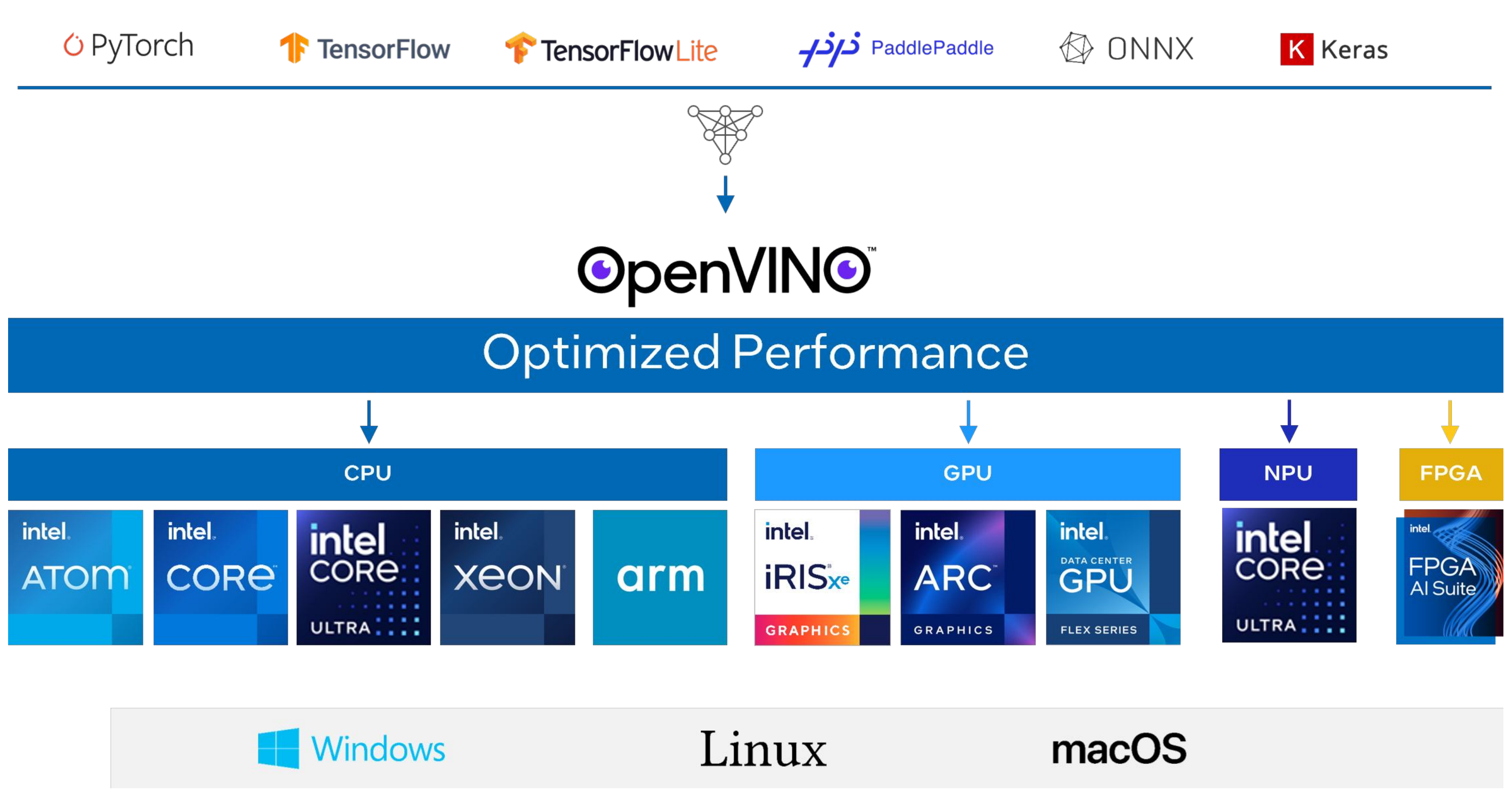
OpenVINO accelerates inference and simplifies deployment across hardware, with a "build once, deploy everywhere" philosophy. To accomplish this, OpenVINO supports + integrates with frameworks (like PyTorch) and offers advanced compression capabilities.

Build your model in the training framework or grab a pre-trained model from Hugging Face

Optimize your model for faster responses & smaller memory

Deploy the same model across hardware, leveraging automatic performance enhancements

Leverage the hardware's AI acceleration by default



OpenVINO Installation

Linux install | Windows install | macOS install

PyPI example for Linux, macOS & Windows:

```
#set up python venv
python -m pip install openvino
```

The install table also has: APT, YUM, Conda, vcpkg, Homebrew, Docker, Conan, & npm

Interactive Notebook Examples

Test out 150+ interactive Jupyter notebooks with cutting-edge open-source models.
Includes model compression, pipeline details, interactive GUIs, and more.
Try out top models for a range of use cases, including:

LLMs | Multimodal | Image Generation | Transcription | Computer Vision

Setup: | Windows | Ubuntu | macOS | RedHat | CentOS | AzureML | Docker | SageMaker

Model Compression with NNCF

NNCF is OpenVINO's deep learning model compression tool, offering cutting-edge AI compression capabilities, including:

1. **Quantization**: reducing the bit-size of the weights, while preserving accuracy
2. **Weight Compression**: easy post-training optimization for LLMs+
3. **Pruning for Sparsity**: drop connections in the model that don't add value
4. **Model Distillation**: a larger 'teacher' model trains a smaller 'student' model

Compression results in smaller and faster models that can be deployed across devices.

Easy install: `pip install nncf`

Documentation | GitHub | NNCF Notebooks | NNCF + Hugging Face

PyTorch + OpenVINO Options

PyTorch models can be directly converted within OpenVINO™:

```
import openvino as ov
import torch
model = torch.load("model.pt") # Convert model loaded from PyTorch file
model.eval()
ov_model = ov.convert_model(model)
core = ov.Core()
compiled_model = core.compile_model(ov_model) # Compile model from memory
```

Or, you can use the OpenVINO backend for torch.compile:

```
import openvino.torch
import torch
# Compile PyTorch model #
opts = {"device" : "CPU", "config" : {"PERFORMANCE_HINT" : "LATENCY"}}
compiled_model = torch.compile(model, backend="openvino", options=opts)
```

Direct conversion | PyTorch Backend | Examples | Blog

Performance Features

OpenVINO can do automatic performance enhancements at runtime customized to your hardware (preserving model accuracy), including:

Asynchronous execution, batch processing, tensor fusion, load balancing, dynamic inference parallelism, automatic BF16 conversion, and more.

Creates a smaller memory footprint of framework + model improving edge deployments.

There are also optional security features: the ability to compute on an encrypted model.

Additional advanced performance features:

- Automatic Device Selection (AUTO) selects the best available devices for the job and may run inference on several of them in parallel.
- Heterogeneous Execution (HETERO) efficiently splits inference between cores
- Automatic Batching ad-hoc groups inference requests for max memory/core utilization
- Performance Hints auto-adjusts runtime parameters to prioritize latency or throughput
- Dynamic Shapes reshapes models to accept arbitrarily-sized inputs, for data flexibility
- Benchmark Tool characterizes model performance in various hardware and pipelines

Supported Hardware

OpenVINO supports CPU, GPU, and NPU. (Specifications)

CPU
intel ATOM
intel CORE
intel CORE ULTRA
intel XEON
arm
GPU
intel iRIS Xe GRAPHICS
intel ARC GRAPHICS
intel DATA CENTER GPU FLEX SERIES
NPU
intel CORE ULTRA
FPGA
intel FPGA AI Suite

The plugin architecture of OpenVINO enables development and plug-independent inference solutions dedicated to different devices. Learn more about the Plugin, OpenVINO Plugin Library, and how to build one with CMake.

Additional community-supported plugins for Nvidia, Java and Rust can be found here.

OpenVINO can Accelerate as a Backend

If you want to stay in another framework API, OpenVINO provides accelerating backends:

PyTorch

```
import openvino.torch
#compile PyTorch model as usual with PyTorch
compiled_model = torch.compile(model, backend="openvino", options =
{"device" : "CPU"})
```

ONNX Runtime

```
onnx_model = onnx.load("model.onnx")
onnx.save_model(onnx_model, 'saved_model.onnx’)
sess.set_providers([‘OpenVINOExecutionProvider’])
```

Hugging Face

```
from optimum.intel import OVModelForCausalLM
#define model_id, use transformers tokenizer & pipeline
model = OVModelForCausalLM.from_pretrained(model_id)
pipe = pipeline("text-generation", model=model, tokenizer=tokenizer)
```

Nvidia Triton

```
$ docker run --rm -p 8000:8000 -p 8001:8001 -p 8002:8002 -v /path/to/
model_repository:/models nvcr.io/nvidia/tritonserver:<xx.yy>-
py3 tritonserver --model-repository=/models
```

Config File:

```
name: "model_a"
backend: "openvino"
```

LangChain

```
ov_llm=HuggingFacePipeline.from_model_id(…backend="openvino",
        model_kwargs={"device":"CPU","ov_config": ov_config})
ov_chain = prompt | ov_llm
print(ov_chain.invoke({"question":“what is neurobiology?”}))
```

Hugging Face Integration

Hugging Face + Intel Optimum offers OpenVINO integration with Hugging Face models and pipelines. You can grab pre-optimized models and use OpenVINO compression features & Runtime capabilities within the Hugging Face API.

Here is an example with an LLM (from this notebook) on how to swap default Hugging Face code for optimized OpenVINO-Hugging Face code:

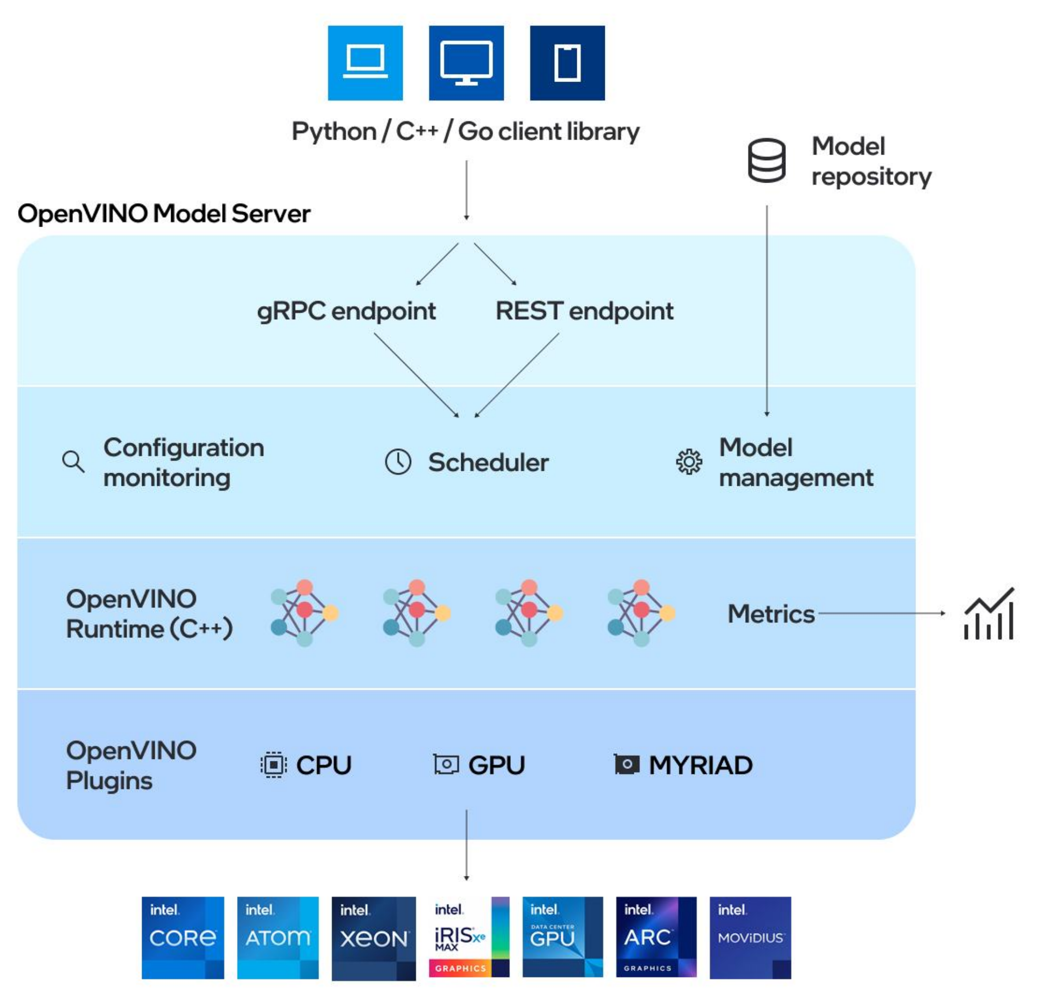
```
-from transformers import AutoModelForCausalLM
+from optimum.intel.openvino import OVModelForCausalLM
from transformers import AutoTokenizer, pipeline
model_id = “togethercomputer/RedPajama-INCITE-Chat-3B-v1”
-model = AutoModelForCausalLM.from_pretrained(model_id)
+model = OVModelForCausalLM.from_pretrained(model_id, export=True)
```

Inference Documentation | Compression Documentation | Reference Documentation | Examples

OpenVINO™ Model Server (OVMS)

OVMS hosts models and makes them accessible to software components over standard network protocols: a client sends a request to the model server, which performs model inference and sends a response back to the client.

OVMS is a high-performance system for serving models. Implemented in C++ for scalability and optimized for deployment on Intel architectures, the model server uses a KServe standard, while applying OpenVINO for inference execution. Inference service is provided via gRPC or REST API, making deploying new models/experiments easy.



Documentation | QuickStart Guide | Features | Demos

Join the OpenVINO Community

We welcome code contributions and feedback! Submit on GitHub and engage on GitHub discussions or our forum. Share your examples (via PR) to be featured here.