



Cognitive Al for the Future: Multimodal Models and RAG in Vision Language Applications, from Training to Deployment

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intel ai

Outline of the tutorial

- Module 0: Motivations, general overview
- Module 1: Accelerate your dataset preparation locally— OpenVINO fundamentals
- Module 2: Fine-tuning the multimodal embedding and VLM
- Q&A
- Module 3: Optimize and deploy the multimodal RAG pipeline
- Module 4: Build your own cognitive AI assistant with multi-agent workflow and multimodal RAG
- Q&A





Cognitive AI for the Future: Multimodal Models and RAG in Vision Language Applications, from Training to Deployment

Module 0:

Cognitive Al: Multimodal RAG in Vision Language Applications

Speaker: Raymond Lo, Zhuo Wu

Job title: AI Software Evangelist



Outline

- What is Cognitive AI? Motivations & Quick Demo
- Multimodal RAG pipeline
- Multimodal RAG with agentic workflow

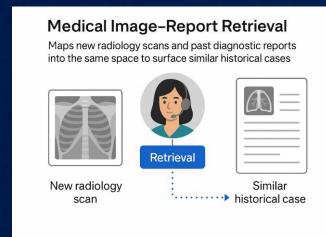


Cognitive Al for the Future

- Learn from multimodal sources
- Learn understanding and reasoning
- Enhance decisionmaking
- Automate complex tasks









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Powered by OpenVINO + MCP Tools



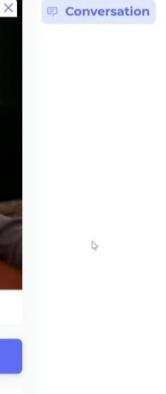
ب ب

2) Build Vector Store

Vector Store is Ready

Agent's Reasoning Log

M Your Actions / Cart



Type your message... Send

Stop

Clear

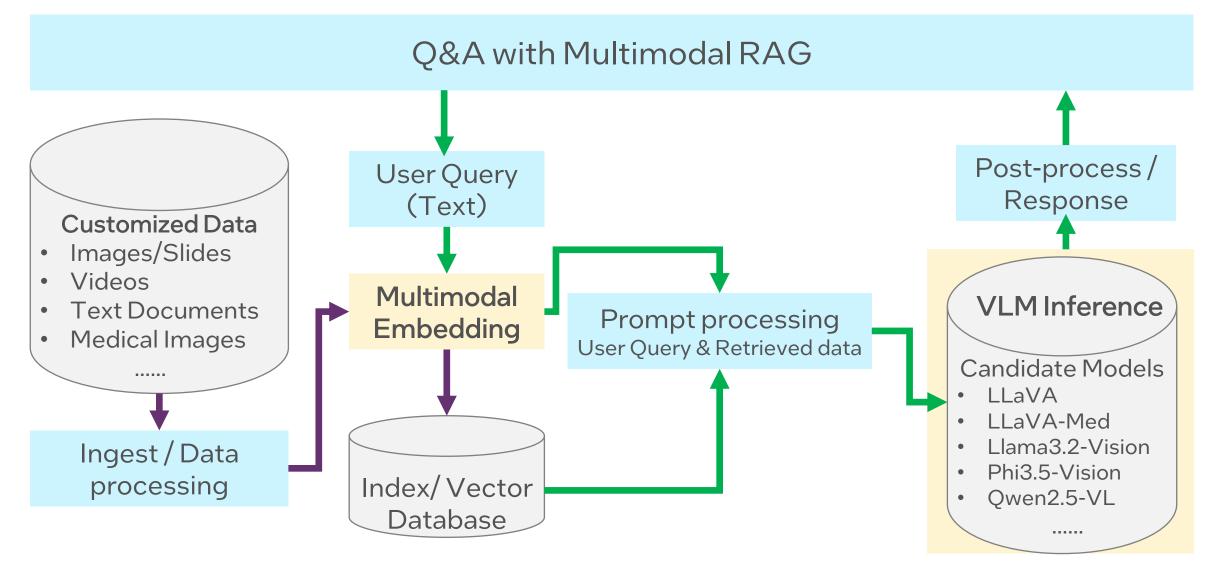
≡ Click example, then Send

What dessert is included in this video?



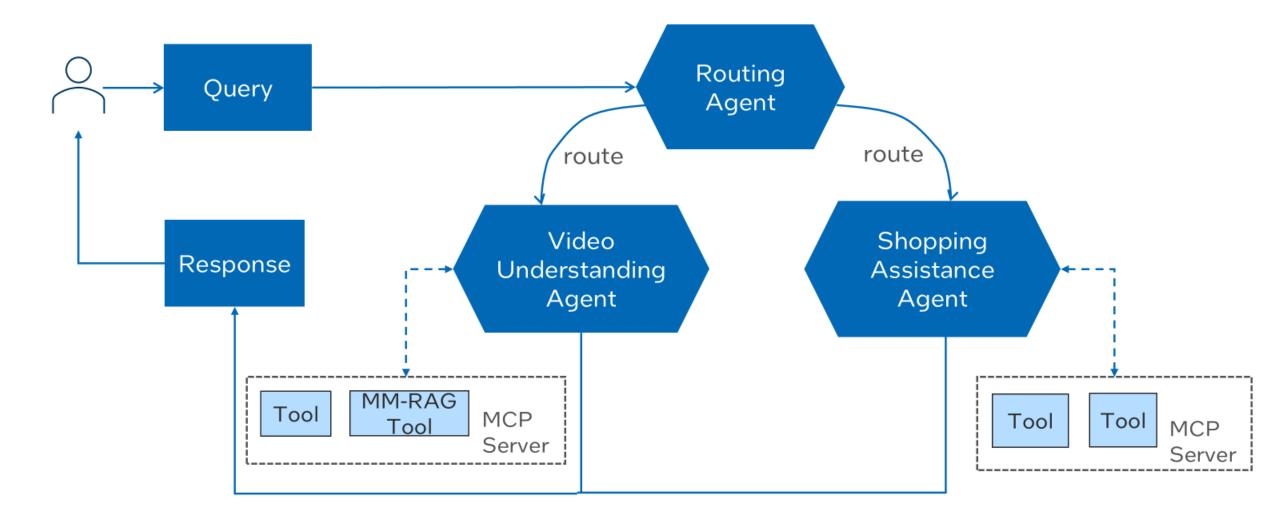
Multimodal RAG Pipeline



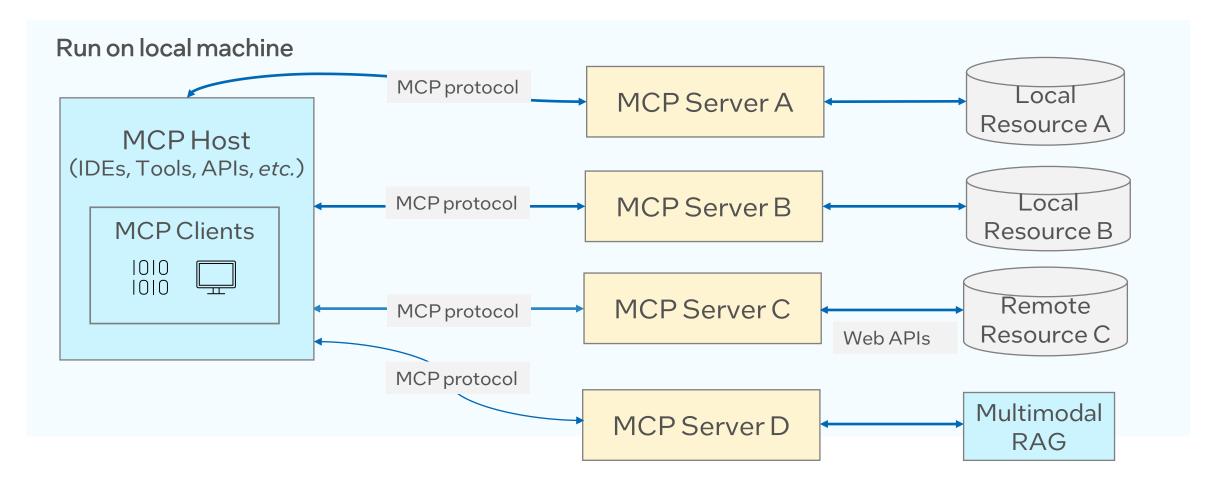


Agentic Workflow with RAG & OpenVINO Tell me about Tool Action Al Response Tool (With tool info) Al Agent RAG LLM with OpenVINO + LangChain/LlamaIndex/ **Qwen-Agent**

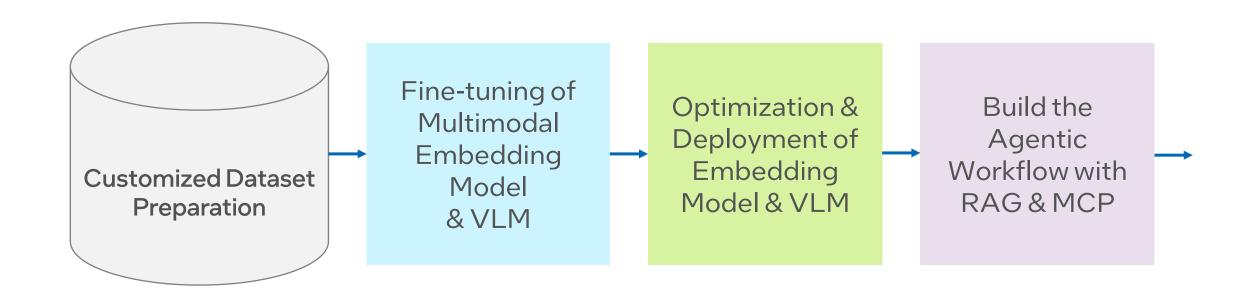
Multi-agent Workflow with RAG & OpenVINO



Multimodal RAG with Agentic Workflow



How to Build Such an Agentic Workflow, from Training to Deployment?



What You Will Learn

Dataset Preparation Model Fine-tuning Optimize & Deploy Agentic Multimodal RAG

- Module 1: Tool for accelerating your dataset preparation locally
- Module 2: How to fine-tune the multimodal embedding model and VLM

- Module 3: How to optimize and deploy the multimodal RAG pipeline
- Module 4: How to build Agentic multimodal RAG

Thank You





Cognitive AI for the Future: Multimodal Models and RAG in Vision Language Applications, from Training to Deployment

Module 1:

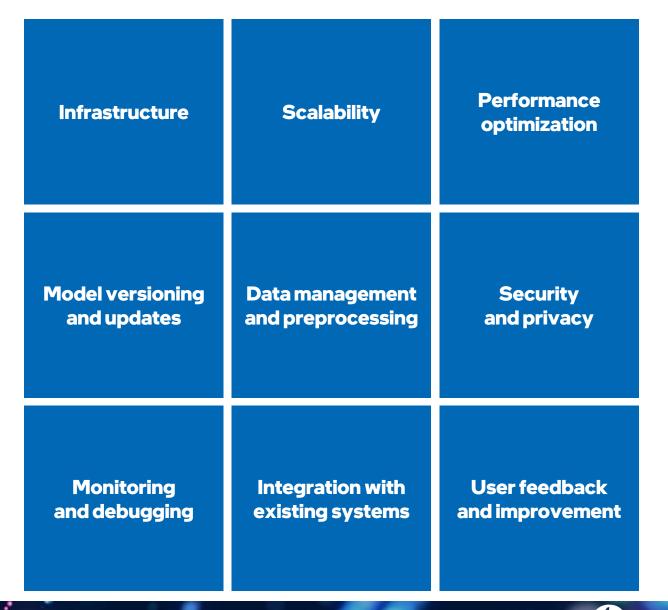
Accelerate your dataset preparation locally: OpenVINO Fundamentals

Speaker: Adrian Boguszewski

Job title: AI Software Evangelist



Deploying Challenges





Deploying Challenges







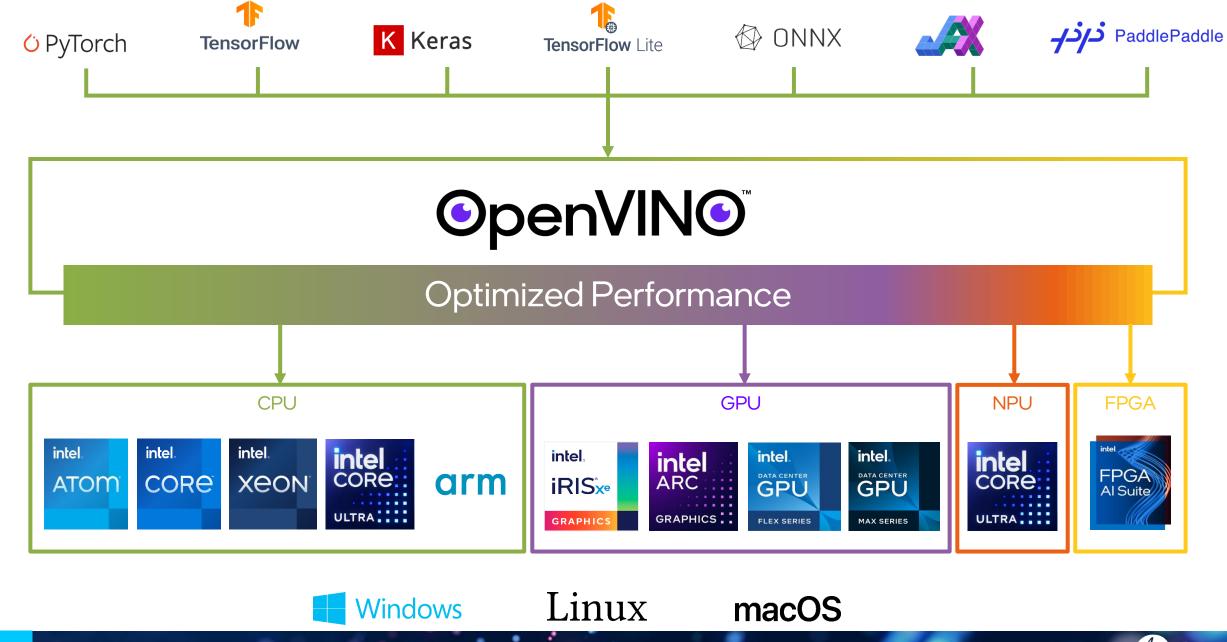


Open/INO and Neural Network Inference **Optimization** Visual+ NLP, Audio, LLM, GenAl, Transformers...

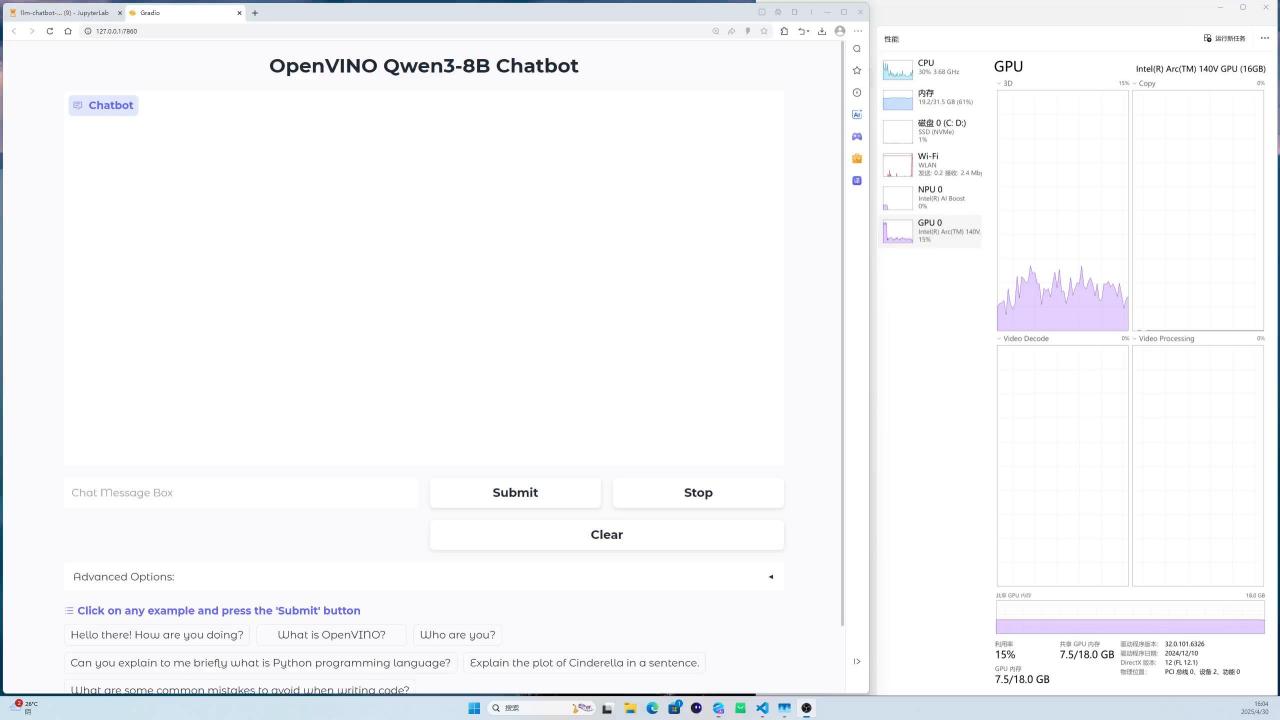


Powered by oneAPI





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Installation

pip install openvino













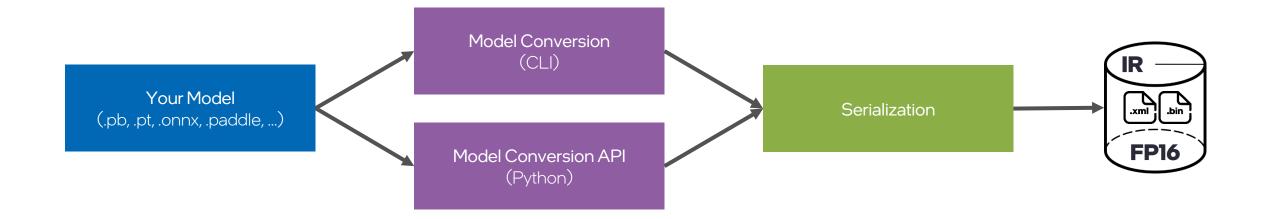


www.openvino.ai



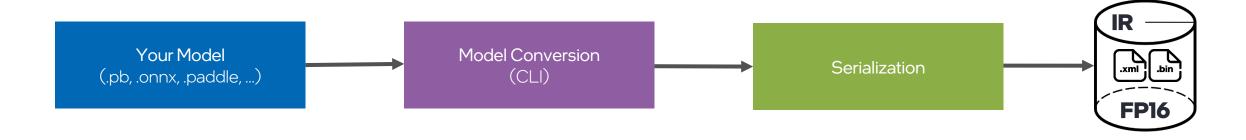
OpenVINO[™] Model Converter





OpenVINO[™] Model Converter



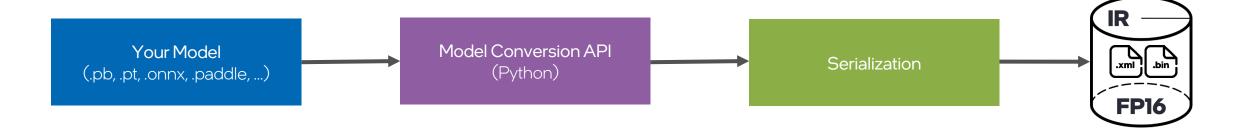


ovc "model.onnx" --input "1,3,224,224"



OpenVINO[™] Model Converter

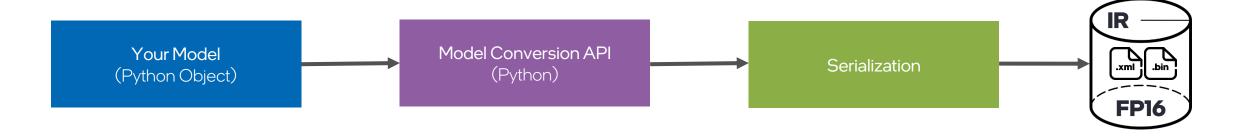






OpenVINO™ Model Converter





OpenVINO™ Runtime



```
from openvino import runtime as ov

img = load_img()

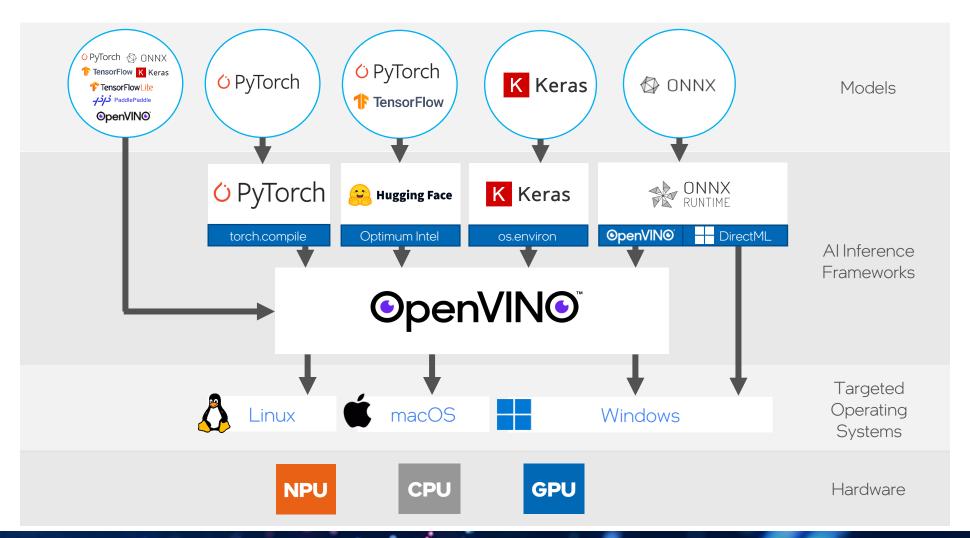
core = ov.Core()

model = core.read_model(model="model.xml")
compiled_model = core.compile_model(model=model, device_name="CPU")

output_layer = compiled_model.outputs[0]

result = compiled_model(img)[output_layer]
```

OpenVINO[™] as Backend



OpenVINO™ Integration with Optimum





Combine the convenience of Hugging Face API with the efficiency of OpenVINO™!



OpenVINO™ Integration with Optimum



```
pip install optimum-intel[openvino,nncf]
```

```
from transformers import AutoModelForCausalLM
from optimum.intel import OVModelForCausalLM
from transformers import AutoTokenizer, pipeline
model id = "OpenVINO/TinyLlama-1.1B-Chat-v1.0-int8-ov"
model = AutoModelForCausalLM.from pretrained(model id)
model = OVModelForCausalLM.from pretrained(model id)
tokenizer = AutoTokenizer.from pretrained(model id)
pipe = pipeline("text-generation", model=model, tokenizer=tokenizer)
results = pipe("He's a dreadful magician and")
```

OpenVINO[™] Integration with Optimum



	Hugging Face through OpenVINO	OpenVINO Native API	
Model support	Broad set of Models	Broad set of Models	
APIs	Python (Hugging Face API)	Python, C++ (OpenVINO API)	
Model Format	Source Framework / OpenVINO	OpenVINO	
Inference code	Hugging Face based	Custom inference pipelines	
Additional dependencies	Many Hugging Face dependencies	Lightweight (e.g. numpy, etc.)	
Application footprint	Large	Small	
Pre/post-processing and glue code	Available at Hugging Face out-of-the-box	OpenVINO samples and notebooks	
Performance	Good	Best	



OpenVINO™ Integration with Optimum

Export to OpenVINO



```
optimum-cli export openvino --model gpt2 ov model
from optimum.intel import OVModelForCausalLM
model id = "OpenVINO/TinyLlama-1.1B-Chat-v1.0-int8-ov"
model = OVModelForCausalLM.from pretrained(model id)
```

```
from optimum.intel import OVModelForCausalLM
model id = "TinyLlama/TinyLlama-1.1B-Chat-v1.0"
model = OVModelForCausalLM.from pretrained(model id, export=True)
model.save pretrained("ov model")
```

Neural Network Compression Framework

(NNCF)









OpenVINO

Native Model Compressed Model Optimization Techniques Post-Training Quantization Accuracy-Control Quantization Quantization-Aware Training Weight Compression Filter Pruning Binarization Sparsity Broad model support Easy Installation pip install nncf



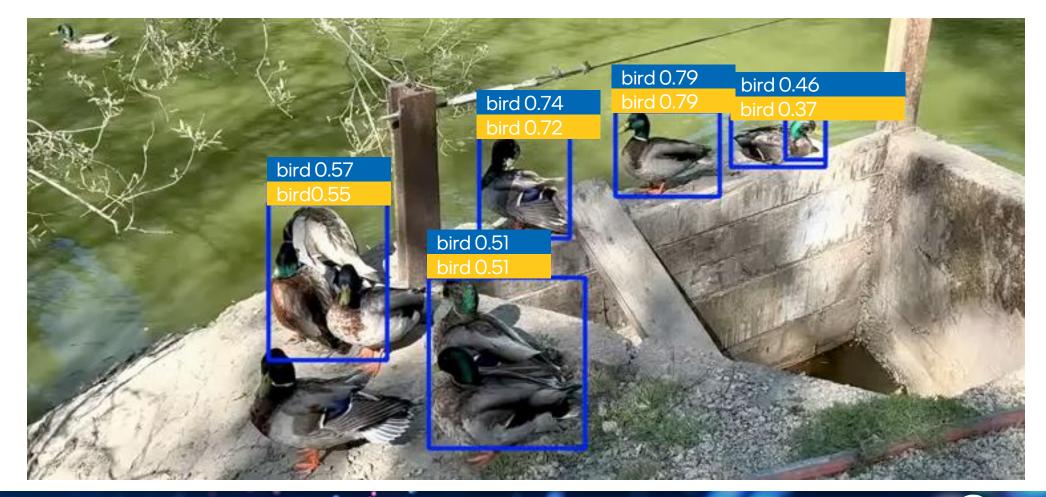
Quantization Performance Optimization

YOLOv8: Minimum accuracy drop from FP32 to INT8



FP32

INT8



Quantization Performance Optimization

OpenPose: Reduced file size and faster inference with consistent accuracy



Native Model

File size: 16.6 MB

Optimized Mode

File size: 4.7 MB

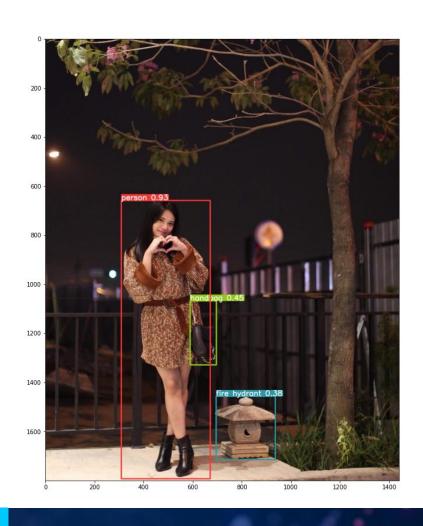




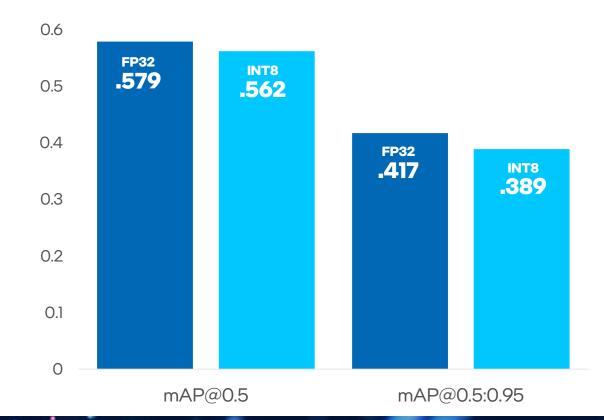
Post-Training Quantization

(NNCF)





Compare YOLOv8 FP32 and INT8 Mean Average Precision









(NNCF)

Model	Mode	Perplexity	Perplexity Increase	Model Size (GB)
databricks/dolly-v2-3b	fp32	5.01	0	10.3
databricks/dolly-v2-3b	int8	5.07	0.05	2.6
databricks/dolly-v2-3b	int4_asym_g32_r50	5.28	0.26	2.2
databricks/dolly-v2-3b	nf4_g128_r60	5.19	0.18	1.9
meta-llama/Llama-2-7b-chat-hf	fp32	3.28	0	25.1
meta-llama/Llama-2-7b-chat-hf	int8	3.29	0.01	6.3
meta-llama/Llama-2-7b-chat-hf	int4_asym_g128_r80	3.41	0.14	4.0
meta-llama/Llama-2-7b-chat-hf	nf4_g128	3.41	0.13	3.5
togethercomputer/RedPajama-INCITE-7B-Instruct	fp32	4.15	0	25.6
togethercomputer/RedPajama-INCITE-7B-Instruct	int8	4.17	0.02	6.4
togethercomputer/RedPajama-INCITE-7B-Instruct	nf4_ov_g32_r60	4.28	0.13	5.1
togethercomputer/RedPajama-INCITE-7B-Instruct	int4_asym_g128	4.17	0.02	3.6

Significant Reduction in RAM usage!



OpenVINO™ Integration with Optimum

Quantization with NNCF



```
from optimum.intel import OVModelForCausalLM
# INT8 quantization
quantization config = OVWeightQuantizationConfig(bits=8)
model = OVModelForCausalLM.from pretrained(model id,
                                           quantization config=quantization config)
from optimum.intel import OVModelForCausalLM
from nncf import compress weights, CompressWeightsMode
# INT4 quantization
quantization config = OVWeightQuantizationConfig(bits=4, sym=True,
                                                 ratio=0.8, group size=128)
model = OVModelForCausalLM.from pretrained(model id,
                                           quantization config=quantization config)
```

GenAl Workflow

Find

Optimize

Deploy



+

O PyTorch



+

OpenVINO & NNCF







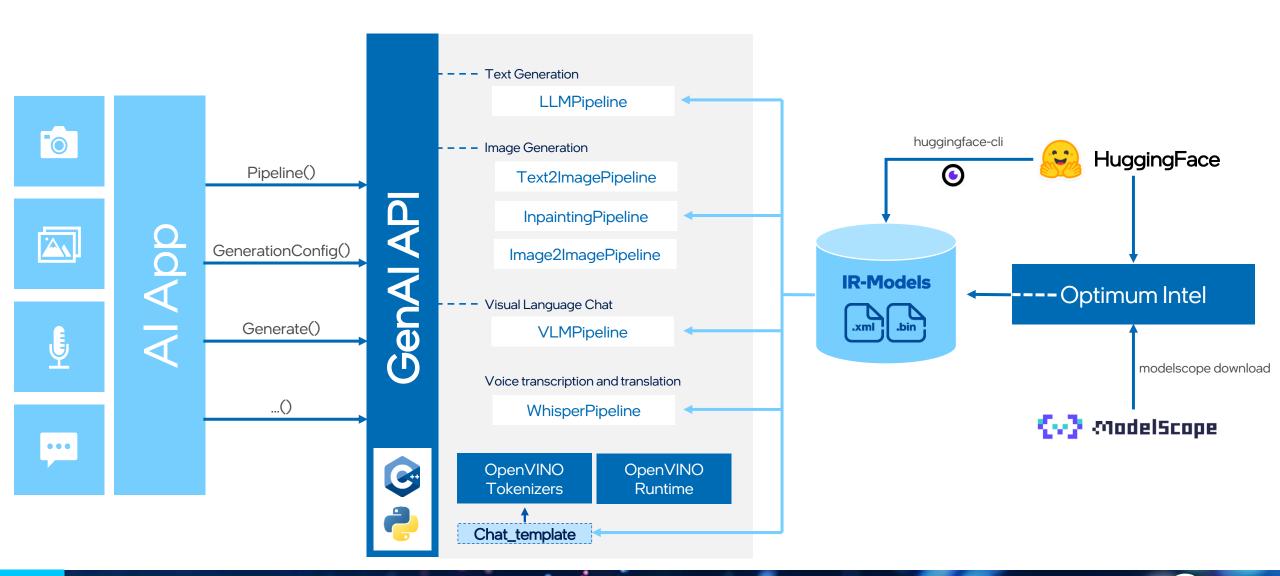


Efficient deployment, minimum dependency and memory footprint



python

OpenVINOTM GenAl





OpenVINOTM GenAl GenAl Model Workflow

Export and optimize pipeline



Hugging Face



huggingface-cli download "OpenVINO/FLUX.1-schnell-int4ov" --local-dir model_path

optimum-cli export openvino --model meta-llama/Llama-2-7b-chat-hf --weight-format int4 ov_llama_2

modelscope download --model 'Qwen/Qwen2-7B-Instruct'
--local_dir model_path

optimum-cli export openvino -m model_path --task textgeneration-with-past --weight-format int4 ov_qwen_2

Deploy pipeline

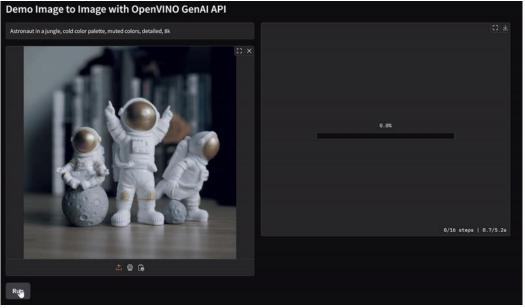




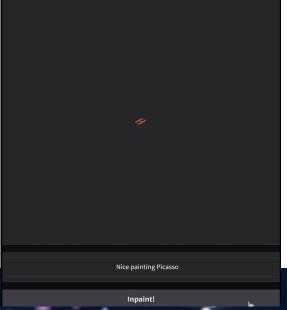


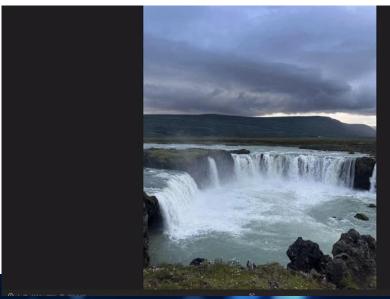
$More\ with\ Open VINO^{TM}\ Gen AI$













Benefits of Building Applications with OpenVINOTM



Build and deploy Al applications in simple steps



Faster inference speed



Maximize Al performance across CPU, GPU, NPU



Smaller model and binary size



Reduce memory footprint



Ability to scale to many nodes with serving

What's next?



What You Will Learn

Dataset Preparation Model Fine-tuning Optimize & Deploy Agentic Multimodal RAG

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