

What's Next in On-Device Generative Al

Jilei Hou

Vice President, Engineering Qualcomm Technologies, Inc.

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Today's agenda



Trends in generative AI and why on device is key

Efficiency techniques to bring generative AI on device

Toward agents and embodied AI at the edge

Q&A

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Multi-camera and LIDAR aligned for bird's-eye-view

Enable enhanced perception of the world for autonomous vehicles, robots, and more using cross-view attention

Wireless multimodal fusion in deepSense 6G

Understand environments better by combining GPS, camera, and mmWave RF using transformers to improve mmWave beam management

Robotics with GATr

Enable robots to efficiently learn complex dexterous skills in 3D spaces from cameras through use of geometric algebra transformers (GATr)



MODALITY AND USE CASE CAPA Voice UI Voice is a natural and intuitive interface for conversation Image: Capability of the capability of t

Video & 3D

Generating content for a richer and more realistic experience

CAPABILITY AND KPI

Longer context window Allows in-depth conversations

Personalization

Fine-tuned models customized to consumers, enterprises, or industries (e.g., LoRA)

Higher resolution

Process higher fidelity images for better accuracy

Agents

Execute multi-step tasks with reasoning autonomously to achieve a goal

increase

To scale, the center of gravity of AI processing is moving to the edge



Hybrid AI

Distribute workloads among cloud and edge/devices to deliver more powerful, efficient, and highly optimized experiences



Central cloud

Ease of development & deployment Training | Very large models Aggregation | Absolute performance

Edge cloud (on-prem or nearby)

Immediacy | Reliability | Personalization | Privacy | SecurityFine-tuning | Aggregation

On device

Immediacy | Reliability | Personalization | Privacy | Security Cost | Energy





Advancements in edge platforms for generative Al and transformers

Multiple axes to optimize AI models and efficiently run them on hardware

Distillation

Learning weights for a smaller student model, which mimic a larger teacher model

Quantization & compression

Learning to reduce bit-precision while keeping desired accuracy

Speculative decoding

Utilizing a large model in concert with a draft model for a faster token rate

Efficient image & video architecture

Designing smaller neural networks that are on par or outperform original architecture

Heterogeneous computing

Utilizing the best processor for diverse AI workloads to improve efficiency

Improving transformer quantization accuracy by reducing outliers



Many modern transformers learn big activation outliers, making them difficult to quantize

This holds for many tasks, training objectives, and models (language encoders/ decoders and vision transformers)

Goal: Address the root cause of the issue and propose a new pre-training protocol to dampen the outliers



Helping attention heads do nothing¹

Strong outliers are related to behavior of attention heads trying to learn "no-op" or a partial update of the residual

To achieve exact zeros in the attention matrix for a no-op, the input to softmax is pushed to be larger and larger during training, causing outliers

> FFN: feed forward network; 1: Quantizable Transformers: Removing Outliers by Helping Attention Heads Do Nothing, NeurIPS 2023,

Our pretraining methods significantly reduce outliers and improve post-training quantization (PTQ) accuracy



Our proposed methods (training from scratch) applied to BERT-base, OPT-125m and ViT-S/16

Two independent modifications to the attention mechanism allow representing exact zeros (and ones)

- 1. Clipped softmax
- 2. Gated attention

Easy to integrate into any transformer model with softmax attention

Quantizable Transformers: Removing Outliers by Helping Attention Heads Do Nothing, NeurIPS 2023, https://export.arxiv.org/abs/2306.12929

	Model	Method	FP16/32	Max inf. norm	Avg. kurtosis	W8A8
	BERT (ppl.↓)	Vanilla	4.49 ^{±0.01}	735 ^{±55}	3076 ^{±262}	1249 ^{±1046}
		Clipped softmax	4.39 ^{±0.00}	21.5 ±1.5	80 ^{±6}	4.52 ^{±0.01}
		Gated attention	$4.45^{\pm 0.03}$	39.2 ^{±26.0}	201 ^{±181}	$4.65^{\pm 0.04}$
	OPT (ppl.↓)	Vanilla	15.84 ± 0.05	340 ^{±47}	$1778^{\pm 444}$	21.18 ^{±1.89}
		Clipped softmax	16.29 ^{±0.07}	$63.2^{\pm 8.8}$	19728 ^{±7480}	37.20 ^{±2.40}
		Gated attention	15.55 ^{±0.05}	8.7 ^{±0.6}	18.9 ^{±0.9}	16.02±0.07
	ViT (acc.↑)	Vanilla	80.75 ^{±0.10}	359 ^{±81}	$1018^{\pm 471}$	69.24 ^{±6.93}
		Clipped softmax	80.89 ^{±0.13}	73.7 ^{±14.9}	22.9 ^{±1.6}	79.77 ^{±0.25}
		Gated attention	81.01 ^{±0.06}	79.8 ^{±0.5}	19.9 ^{±0.3}	79.82 ^{±0.11}
Clipped softmax and gated attention are our techniques. ppl. = perplexity; acc. = accuracy		On par or ightly better oating-point erformance	Significantly reduced both outlier magnitude and kurtosis		Significantly better PTQ INT8 performance	

Vector quantization (VQ) shrinks models while maintaining desired accuracy



Employing non-linear quantization and expanding the dimensionality of the representational grid through VQ



"GPTVQ: The Blessing of Dimensionality for LLM Quantization", van Baalen et al., ICML 2024, <u>https://arxiv.org/abs/2402.15319v1</u>. VQ feature is coming to AI Model Efficiency Toolkit (AIMET). AIMET is a product of Qualcomm Innovation Center, Inc.

VQ can improve footprint and latency for memory-bound generative AI like LLMs

Setting	BPV ↓	Relative ↓ footprint	Relative ↓ latency
INT4	4	1.00x	1.00x
INT8	8	2.00x	1.93x
2D 2.5B @b512	3	0.75x	0.98x
2D 2.5B @b2048	2.25	0.56x	0.96x
2D 2B @b1024	2.25	0.56x	0.87x
Llamav2-7B 1D 3B @b128	3.5	0.88x	0.96x

Speculative decoding

Speeds up token rate by trading off compute for bandwidth





Draft model generates a few speculative tokens at a time

Target model decides which to accept in one pass

A good draft model predicts with a high acceptance rate

Training the draft model for multimodal LLM speculative decoding

LLaVA as an example of an LMM with vision





LLaVA draft model finetuning

1: Goel, Raghavv, et al. "Direct Alignment of Draft Model for Speculative Decoding with Chat-Fine-Tuned LLMs." (https://arxiv.org/abs/2403.00858v3, 2024); LLaVA: large language and vision assistant; VLM: vision language model

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Applying speculative decoding to LMMs with vision

Achieving higher token rates for LMMs without sacrificing accuracy





Generation example (accepted drafts <u>underlined</u>)



4.0

Input prompt:

A chat between a curious user and an artificial intelligence assistant. The assistant gives helpful, detailed, and polite answers to the user's questions. **USER**: <image> Provide a detailed description of the given image.

Output generation: The image features <u>a</u> close-<u>up of</u> a pink <u>and white</u> fruit, possibly <u>a</u> dragon fruit, with its skin pee<u>led</u> back to <u>reveal</u> the white and <u>black</u> see<u>ds</u> inside. The fruit <u>is</u> placed <u>on a wooden</u> table, and <u>the</u> close-<u>up</u> view highlight<u>s</u> the intricate details of the see<u>ds</u> and <u>the</u> fruit's skin. The dragon fruit is the main focus <u>of the image</u>, and it <u>appears to be</u> the only fruit <u>in the</u> scene.





LLaVA: large language and vision assistant; MBSU: memory-bound speed-up; SD: speculative decoding



WORLD'S FIRST large multimodal model (LMM) on an Android phone





LLMs can now see

7+ billion parameter LMM, LLaVA, with text, speech, and image inputs

Multi-turn intuitive conversations about an image at a responsive token rate

Full-stack AI optimization to achieve high performance at low power

Enhanced privacy, reliability, personalization, and cost with on-device processing

The potential of generative video editing

Given an input video and a text prompt describing the edit, generate a new video



Input video

Key challenges:

- 1. Temporal consistency
- 2. High computational cost



Edited video



Prompt: "pink flamingo walking"

Making generative video methods efficient for on-device AI

Optimizations to FAIRY¹, a video-to-video generative AI model



Stage 1: Extract states from anchor frames



Stage 2: Edit video across remaining frames

1: "FAIRY: Fast Parallelized Instruction-Guided Video-to-Video Synthesis" (https://arxiv.org/abs/2312.13834)

Fast FAIRY results

Making generative video feasible on device through significant reduction in computation and memory



Original video



Turn into a marble roman sculpture



Turn into low poly art



Turn into a metal knight sculpture



Change the style to cartoon



In cubism style



Diverse processors are essential for maximizing performance and power efficiency in generative AI applications





Researching visually-grounded LLMs with the ability to reason and interact with the environment



LLM

Visually-grounded LLM

Orchestrator

Vision

Action

recognition

Fron[®] end

Situated visionlanguage models

- Process a live video stream in real time and dynamically interact with users
- Determine what to say and when to say it
- Enable the path to humanoids

Open-ended, asynchronous interaction with situated agents is an open challenge

- Limited to turn-based interactions about offline documents or images
- Limited to capturing momentary snapshots of reality in a VQA-style dialogue



Our situated visionlanguage model for fitness coaching

- A 3D CNN-based vision backbone for processing the vision stream
- A pretrained Llama2-7B language model backbone to generate interactive feedbacks
- A cross-attention-based adapter deeply fusing the two

Key innovations

- End-to-end training for situated visual understanding
- Processing the vision stream (dynamic vs static)
- Introducing action tokens (when/what to say)
- Pre-training the vision backbone (increased accuracy) Visual stream

3D CNN 3D CNN 3D CNN PROMPT SELF-ATTN SELE-ATTN SELE-ATTN SELF-ATTN SELF-ATTN SELF-ATTN + CROSS-ATTN SELF-ATTN SELF-ATTN CROSS-ATTN CROSS-ATTN CROSS-ATTN SELF-ATTN SELF-ATTN SELF-ATTN SELF-ATTN SELF-ATTN SELF-ATTN SELF-ATTN CROSS-ATTN CROSS-ATTN CROSS-ATTN CROSS-ATTN SELF-ATTN + SELF-ATTN SELF-ATTN SELF-ATTN SELF-ATTN SELF-ATTN SELF-ATTN < next > < next > < next > smooth on

What to Say and When to Say it: Video-Language Model and Benchmark for Situated Interactions (2024)

Leading results





Question: Provide an appropriate feedback for the user

Video-LLaMA: We see a young man standing in a kitchen, wearing a red shirt and white shorts.

Video-ChatGPT: The user has successfully demonstrated the ability to perform a balancing act on a pair of pols.

Coach-LLaMA: This is awesome. Let's keep the intensity high!

Method	T-F-Score ↑	T-BERT ↑	T-Rouge-L ↑	Mixtral-Score ↑
Video-LLaMA	0.57	0.436	0.029	2.39
Video-ChatGPT	0.57	0.439	0.033	2.72
Coach-Llama (ours)	0.64	0.512	0.115	3.10

Aimed at the development of interactive multi-modal vision-language models based in the controlled but challenging fitness coaching domain



FIT-Coach benchmark and dataset

A novel interactive visual coaching benchmark and dataset as a test-bed for real-time, real-world situated interaction

Fitness questions dataset

148 exercises **300k** short-clip videos

1900 unique high-level participants question-answer pairs

470+ hours

400k+ fine-grained question- answer pairs

Fitness feedback dataset

148

exercises

9+ hours of fitness coaching session Haya

~3.5 minutes long sessions with 5 to 6 exercises 21

unique participants

What to Say and When to Say it: Video-Language Model and Benchmark for Situated Interactions (2024)



The path to humanoid robots

We need to take advantage of end-to-end learning





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Generative AI capabilities are evolving and more beneficial on the edge

Advancements in architectures, algorithms, and heterogeneous computing are enabling generative AI on the edge

Generative AI agents and systems allow developers to significantly enhance applications and enable embodied AI

Resources

Booth and live demos

at conference hall 718



Qualcomm AI Hub

https://aihub.qualcomm.com/



2024 Embedded Vision Summit

May 21st (1:00-4:00pm)

"Accelerating Model Deployment with Qualcomm® AI Hub" – Bhushan Sonawane

May 22nd (1:30-2:00pm)

"OpenCV for High-Performance, Low-Power Vision Applications on Snapdragon" – Xin Zhong

May 23rd (9:50-10:20am)

"What's Next in On-Device Generative AI" – Jilei Hou

May 23rd (10:20-11:10am)

"Multimodal LLMs at the Edge: Are We There Yet?" – Jilei Hou (Panel session)

May 23rd (1:30-2:00pm)

"Deploying large models on the edge : Success Stories & Challenges" – Vinesh Sukumar



Thank you

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