Deploying Large Language Models with Ease

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Machine Learning is at a crossroads...

Two issues

LLMs are great! But...



Do you really want to give your **precious data** to big corporations?

ML Projects are lcebergs



Visible to users Focused on by bloggers

Important work to get models in production





Visible to users Focused on by bloggers

Important work to get models in production

LLMs made the iceberg deeper



Icebergs can sink Titanics



Model APIs can shrink your iceberg into an ice cream cone



Hi, I'm Hannes.

Natural Language Processing

standing, analyzing, and generating text with Python

Hobson Lane Cole Howard Hannes Max Hapke Foreword by Dr. Arwen Griffioen

MANNING

O'REILLY®

Building Machine Learning **Pipelines**

Automating Model Life Cycles with TensorFlow



Hannes Hapke & Catherine Nelson Foreword By Aurélien Géron

O'REILLY°

Machine Learning Production Systems



Startup financial operations, powered by Al bookkeeping



How are we using LLMs?

				(New Invoice
Sent		(!) Overdue	Nudge	Paid	₽ Past 30 Days
X XYZ Incorporated Due June 30, 2024	\$400.00	T Trade Connect Due May 1, 2024	\$400.00	H Homebody I Due Mar 30, 20	nc. 024 \$800.00
Total	\$400.00	8 Days Overdue	2	Total	\$800.00
		S Signpost LLC. Due May 30, 2024	\$1,200.00		
		28 Days Overdue			
		Total	\$1,600.00		
	<section-header> Sent XYZ Incorporated Due June 30, 2024 </section-header>	<section-header> ✓ Sent ✓ X/Z Incorporated Dae June 30, 2024 \$400.00 Total \$400.00</section-header>	 Sent XYZ Incorporated Due June 30, 2024 S400.00 Total \$400.00 Bays Overdue Signpost LLC. Due May 30, 2024 Bays Overdue Bays Overdue Bays Overdue Total 	Sent YZ Incorporated Due June 30, 2024 \$400.00 () Overdue () Due May 1, 2024 () May 0.00 () Signpost LLC. () Due May 30, 2024 () Due May 30, 2024 () Signpost LLC. () Due May 30, 2024 () Due May 30, 202	 Sent XYZ Incorporated Due June 30, 2024 \$400.00 Total \$400.00 Signpost LLC. Due May 30, 2024 \$1,200.00 Signpost LLC. Due May 30, 2024 \$1,200.00 ZB Days Overdue Total \$1,600.00



	Google Cloud			0		
	Invoice #: 120325 Issued: 2024-04-30 Due: 2024-05-31	Bill from: Google Cloud 1600 Amphitheatre Parkway Mountain View, CA, 94043 United States invoices@google.com	Bill to: Digits 1355 Market Street San Francisco, CA, United States bills@digits.com	94103		
	Item	Quantity	Unit Cost	Line Total		
	Google Cloud — Production	1	\$37,577.23	\$37,577.23		
Edit Li	ne ltems					
1 Item				Amo	unt	
1 Google Cloud — Production \$37,577.23						
Categ	gory					
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Bill Amount **\$37,577.23** Items Amount \bigcirc \$37,577.23

Understanding Documents



Vendor Details

NameAddressPhoneWebsiteSocial Media LinksWikipedia SiteDescriptionShort DescriptionKeywordsIs a National BrandLogo

All runs in Production.

Why did the iceberg get bigger?

Resource intensive deployments

Constantly changing ML world

Difficult to fine-tune

Evaluation can be tricky

New tooling needed



Lessons Learned



Nodel Selection



Smaller is often better

Complex hosting 70b models

Latency can be a killer to LLMs

Very limited real-world benefits

MoE models seems limited



Focus on a specific model

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Tooling and Infrastructure

GCP Vertex not designed for LLMs

Deployment is 10-100x expensive

CUDA





Inference Optimizations

Parallelization

Efficient Attention

Quantization

Continuous Batching



Paraleization

Multi-GPU / multi-node inference

Quick explosion of costs



Paraleization

Costs increase: 2-5x



Efficient Attention

KV Caching is King/Queen

No recomputation of previous tokens needed

E.g. PagedAttention



Example: 70b Model

Tokens x n_{layers} x n_{kv_heads} x d_{heads} x sizeof(dtype)

Weights: ~130 GiB

KV Cache: ~160 GiB





Quantization

Reduce memory requirements, reduce weights + KV cache





Generalized Post-Training Quantization (GPTQ)

Balanced between compression gains and inference speed

Focuses on GPU inference and flexibility in quantization levels



Activation-Aware Weight Quantization (AWQ)

Observes activations for weight quantization

High quantization performance for instruction-tuned LLMs



Quantitization Costs reduced: 90% Very project specific



Batch	
R1	
R2	
R3	









Continuous Batching



Batching Improvements: 2x Soon: 3-4x



Deployment Strategies

Batching

Easier to host very large LLMs

Less cost intensive



Streaming

Idle time will be expensive

More cost intensive

Latency matters

Users love the immediate results



Other Lessons Learned

Lessons Learned

Users got used to streaming

Serving Streaming Mode is another beast

Latency to first token is less important than overall task completion





Conclusions

Smaller is often better

Consider the model latency

Batching beats Streaming

Don't follow every trend, focus

OS LLMs are a long game



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Thank you!