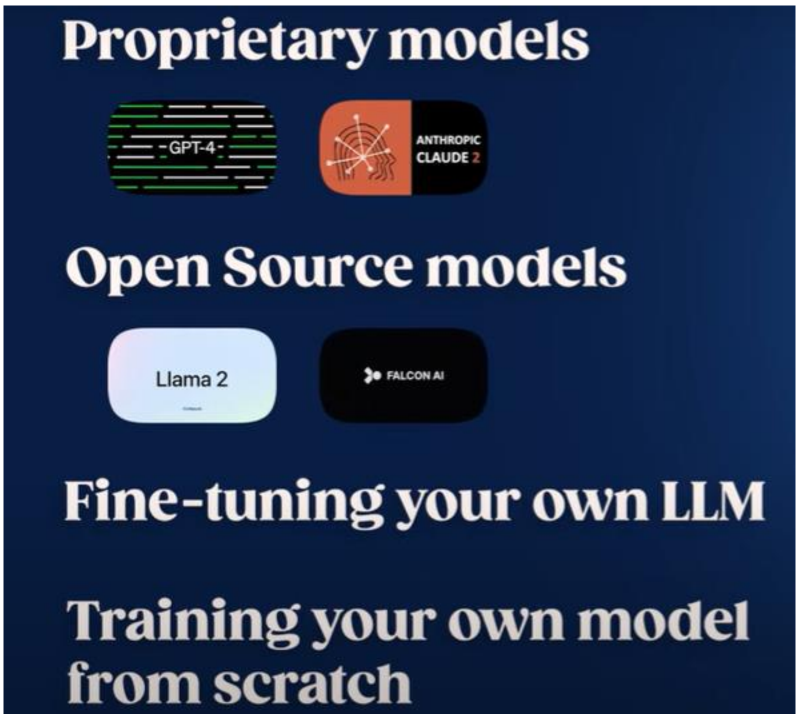
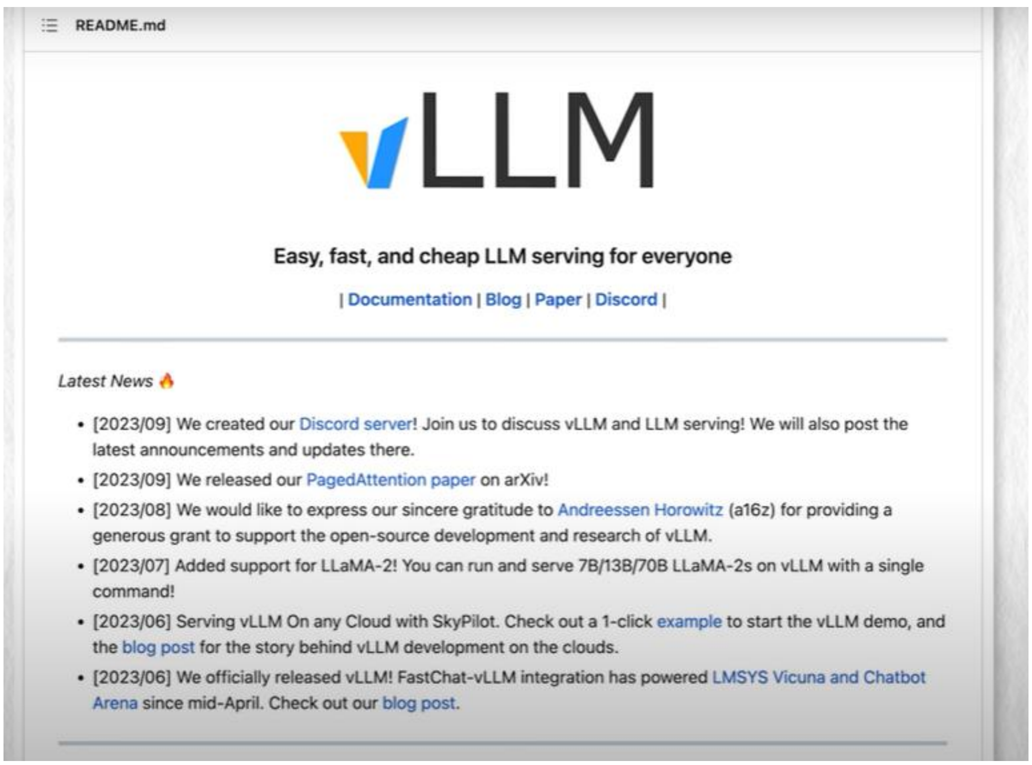
https://youtu.be/Nr3ckDhDfK8

Model Selection phase:



Adaptation Phase:

- **Finetuning**
- **RLHF**
- **RAG**
- **Deep Memory**



README.md

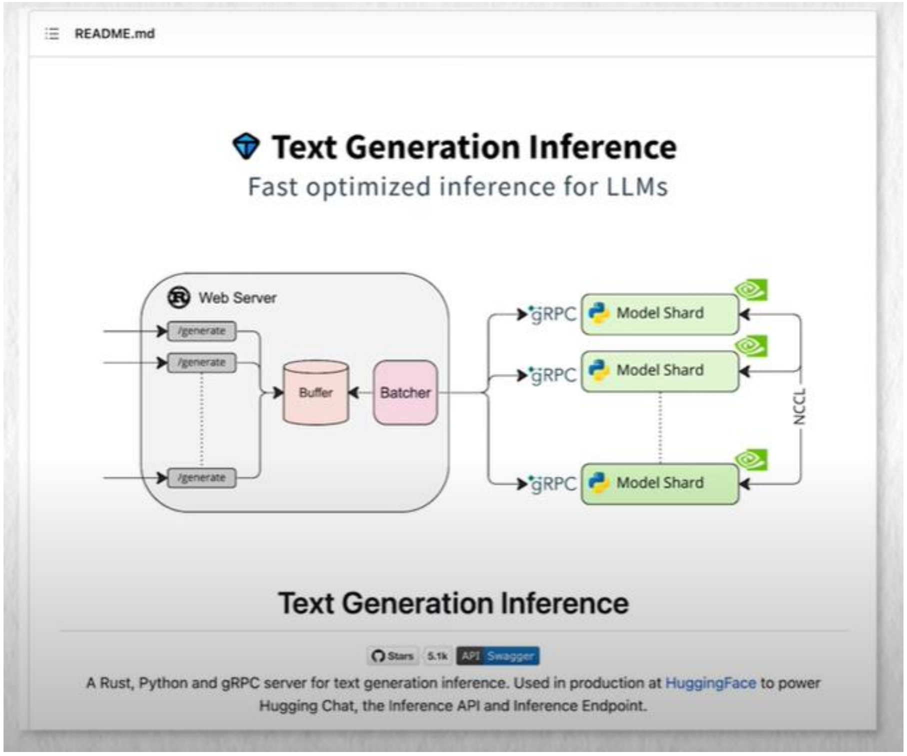
vLLM

Easy, fast, and cheap LLM serving for everyone

| Documentation | Blog | Paper | Discord |

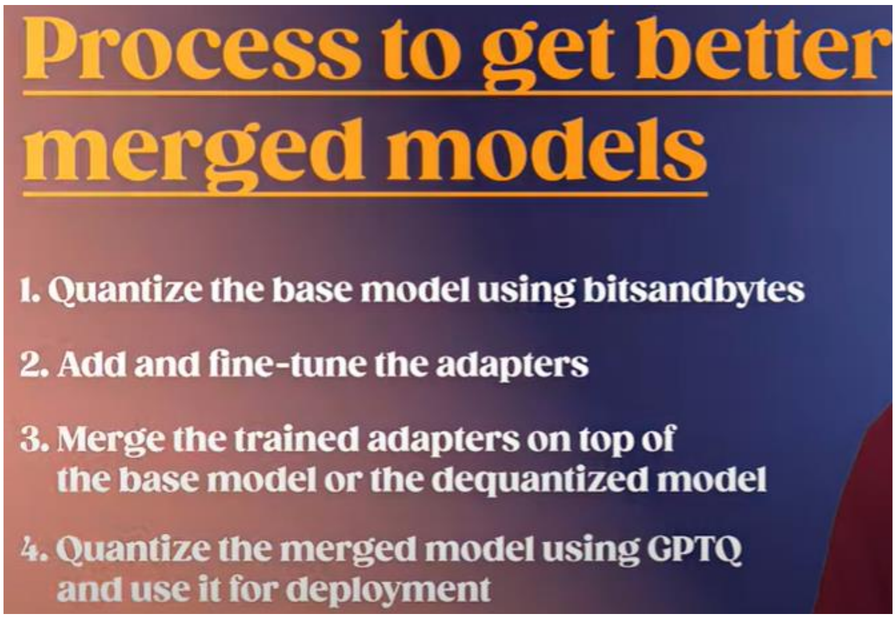
Latest News 🔥

- [2023/09] We created our Discord server! Join us to discuss vLLM and LLM serving! We will also post the latest announcements and updates there.
- [2023/09] We released our PagedAttention paper on arXiv!
- [2023/08] We would like to express our sincere gratitude to Andreessen Horowitz (a16z) for providing a generous grant to support the open-source development and research of vLLM.
- [2023/07] Added support for LLaMA-2! You can run and serve 7B/13B/70B LLaMA-2s on vLLM with a single command!
- [2023/06] Serving vLLM On any Cloud with SkyPilot. Check out a 1-click example to start the vLLM demo, and the blog post for the story behind vLLM development on the clouds.
- [2023/06] We officially released vLLM! FastChat-vLLM integration has powered LMSYS Vicuna and Chatbot Arena since mid-April. Check out our blog post.


README.md
Text Generation Inference
Fast optimized inference for LLMs
Web Server
/generate
/generate
/generate
Buffer
Batcher
gRPC
gRPC
gRPC
Model Shard
Model Shard
Model Shard
NCCL
Text Generation Inference
Stars
5.1k
API
Swagger
A Rust, Python and gRPC server for text generation inference. Used in production at HuggingFace to power Hugging Chat, the Inference API and Inference Endpoint.


Model Distillation
Model Pruning
LLM Model
Model Quantization
Using smaller variants

Introduction to LLMOps



have you ever dreamed of launching a

company built around llms with those
powerful models now easily accessible
they are pretty much the golden ticket
to easily starting your own project in
this video we'll dive into all the steps
required to build your application based
on llms these steps Encompass the
practices commonly used to leverage llms
in production effectively and they are
typically referred to as large language
models operations or llm UPS from the
chat but powered by open eyes chity to
the smart writing assistant you love
like grammarly llms are reshaping almost
all Industries but creating a successful
llm based application is not that easy
it brings unique challenges that differ
from traditional products and even from
other AI based products here are the
five essential steps to Kickstart your
llm Venture which you need to understand
and carefully tackle to successfully
Implement by the way we've built an
entirely free course on training Ing
fine-tuning and deploying llms in
collaboration with tzi active Loop and
the Intel disruptor initiative linked
Below in which you can find Cod and
practical examples for all the steps I'm

discussing in this

video first you need to select the right

Step 1: Model selection phase.

llm for your use case here you have many

different choices from proprietary

models like gp4 by open AI or Cloud by

anthropic open source pre-trained llms

like latu or falcon fine-tuning your own

llm to even training your own model from

scratch which we all cover in our free

llm course train from scratch is very

difficult but it can definitely be a

GameChanger if you have the resource to

do it developers or startups often lean

towards proprietary models from Tech

Giants or open source Alternatives based

on platforms like hugging face

proprietary llms backed by substantial

Investments typically outperforms open

source versions and come with the added

benefit of cost-saving from not needing

to establish expensive inference

infrastructure and from economy of scale

additionally always check an lm's

knowledge cut off which is the last date

it was updated for instance chat GPT

can't discuss event past September 20121

which might lead to inaccurate outputs

on newer topics so it really depends on

your goal but you have many choices
hugging phase manages an online
leaderboard of open-source llms
evaluated on different curated benchmark
marks you may be interested in checking
it out to be always updated on the
latest open

Step 2: Adaptation phase.

llms once you choose a good foundation
model you must tailor it to your use
case once again you have different
options depending on the task I did a
full video to help you solve this exact
problem and better understand which
adaptation technique to use for your
task from F tuning prompting retraining
using reinforcement learning techniques
like rhf or reinforce ment learning from
AI feedback RL aif to using retrieval
augmented generation rag or its more
efficient alternative called Deep memory
from active Loop that we all explain in
detail in our free course to quickly
recap you can use fine tuning when you
want to make your llm an exper on a
specific topic you will want to use deep
memory when you have documentation for
your task that you want the model to use
and not hallucinate answers it's also

much cheaper than fine-tuning and can be
complimentary to it retraining from
scratch is already done but possible if
you want to entirely own your llm and
not rely on other companies and
approaches similar to what Bloomberg did
with Bloomberg GPD rhf and rla aif are
the powerful ways of fine tuning your
model to your task as I said we covered
these approaches in depth in the other
videos of the llm series if you want
more details in selecting the best
approach in your
Step 3: Evaluation phase.
case once your model is ready ready you
need to know how well it performs like
in school you need to compare it with
others using exams in this case the
exams are called benchmarks and just
like a philosophy exam rating the
students is super challenging since the
outputs are text answers which are
mainly subjective you cannot simply
classify the answer and voila it is
right or wrong for example try thinking
about how you could evaluate the quality
of an answer given by an llm assistant
whose job is to summarize YouTube videos
for which you don't have reference

summaries written by humans this is even
harder if your llm is supposed to work
as a general assistant like chat GPT
currently organizations often resort to
AB testing to assess the effectiveness
of their model checking whether the user
satisfaction is the same or better after
the change in production so you
minimally need to use multiple metrics
not just one to have a better overall
idea of the performance of your model
you also surely need qualitative
evaluations which means just play with
it and push it to its limit yourself as
I said you need to test your model on
multiple benchmarks that are related to
the task you want to tackle and compare
the metrics given to other approaches to
be sure you are somewhat competitive and
using the best possible solution at
least the best affordable solution here
again I have a complete video on the
different evaluation benchmarks for llms
and we have super practical examples for
doing that in the course
[Music]
Step 4: Deployment phase.
you now have your powerful model that
beats all others but it does that only

on your computer or remote server the
next step is to share it with the world
and this is called the deployment phase
which comes with lots of challenges from
latency to memory to cuss issues where
you need to make a lot of important
decisions deploying large language
models like GPT variant or any other llm
into real world applications often
requires a multi-stage process
you will integrate it into systems using
cloud-based apis such as Google vertex
AI or Amazon sagemaker or by deploying
the model directly using Frameworks like
tensorflow serving or Onyx all the
specific details will be dependent on
the size of your model and the speed of
responses you are looking for here are a
few challenges to look out for and tips
we gathered for you first compute
resources llms demand high computational
power ensure you have the necessary
infrastructure whether it's cloud-based
Solutions with AWS or Google cloud or
powerful local servers in practice for
smaller llms a standard GPU can be find
indeed an llm with 1 billion parameters
where each parameter is stored as a
float 32 requires 1 billion * 4 BYT

which is 4 GB of memory for inference which is fine for lower-end gpus moreover by leveraging quantization techniques it's possible to store the model parameter ERS with smaller data types like one bytes or 4 bits with small downgrades in performance thus saving even more in memory for example using 4bit quantization we'd be able to use an 8B parameter model on a GPU with 4 GB of R if you're looking at libraries that can help you manage and deploy llms you have the choice of vlm made by a team of researchers and there's also the text generation inference library from the team at hugging face the shear size of llms can make them slow and expensive to run model destillation quantization pruning or using smaller variants can help you mitigate this which you can learn more about in the course model quantization is the simplest option you can apply in order to reduce your infrastructure costs and speed up the inference when using open source llms right now the two popular implementations are bits and bytes and gptq the team at hugging face published a great article comparing the two

methods if you're interested they
conclude that bits and bytes is better
suited for fine-tuning while gptq is
better for Generation from their
observations one way to get better
merged models would be to first quantize
the model using bits and bytes add and
fine-tune the adapters merge the trained
adapters on top of the base model or
quantize the merged model using gptq and
use it for deployment then probably the
most important but underlooked challenge
ethical considerations llms can
sometimes produce biased or
inappropriate outputs continuous
monitoring and establishing ethical
guidelines are crucial you can also use
retrieval augmented approaches to help
mitigate hallucination and bias Problems
by the way I just published a video with
seven tips to help you mitigate that
source of llm Errors if you want to
learn more about that another important
Data privacy!
aspect to consider is data privacy when
fine tuning or doing continuous learning
on specific data ensure that user data
privacy is maintained and that you are
compliant with regulations like gdpr

speaking of continuous learning while
llms have fast knowledge they don't
learn from new data after deployment
unless retrained implementing a
continuous learning process can help
keep the model updated and increasingly
powerful you won't have the usual as of
my last update in September 2021 I do
not have realtime data about events or
elections that occurred after that point
message anymore if you you deployed your
model and checked for all these sources
of problems congrats the model is now
live and running but your work isn't
done
here you still need to monitor how your
Step 5: Monitoring phase.
model is performing online with new user
requests you will have bugs and
unexpected behavior that is for sure so
you need systems in place to visualize
and inspect the execution flow of your
LM analyze the inputs and outputs view
intermediate results and securely manage
prompts and and llm chain configurations
thankfully there are amazing companies
helping you do that and one that I
personally use is weights and biases and
more specifically weights and biases

prompts which offers a set of features
for developers to do all that you can
use any software you want but make sure
to track the llm and not let it be out
there it could scale up pretty quickly
and hurt lots of people again if you
want more information on that check out
the llm apps section of our course or
wait and biases directly mastering llm
Conclusion.
UPS is necessary for navigating the llm
based business landscape we've quickly
covered all the steps required to build
deploy and refine applications powered
by these AI Jugger notes but the
landscape is evolving quickly and
continuously so you must equip yourself
with the right tools and stay up to date
if this piqued your interest and you are
hungry for handson insights dive deeper
with our comprehensive course in
collaboration with 2zi active Loop and
the Intel disruptor initiative I hope
you've enjoyed this video of our llm
series stay tuned for more llm insights
in my upcoming
[Music]
[Music]
videos