

Adapting Large Language Models to Arbitrary Domains Using Retrieval Augmented Generation (RAG)





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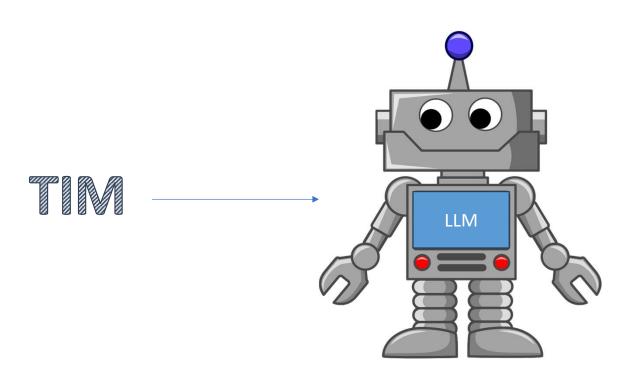


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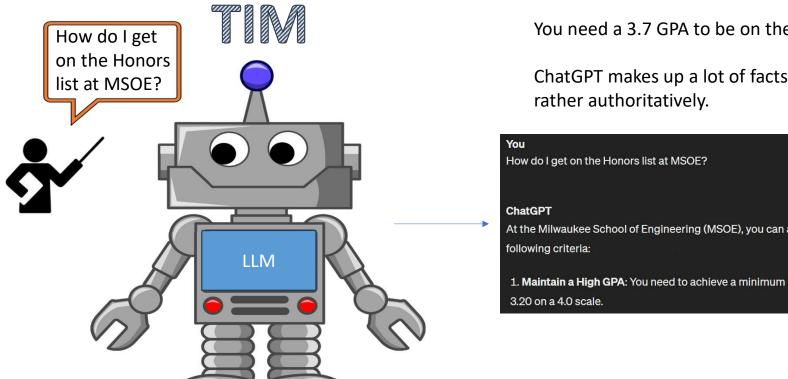


Tyler Cernik (CS)

The final member of our group



The problem with just using Tim

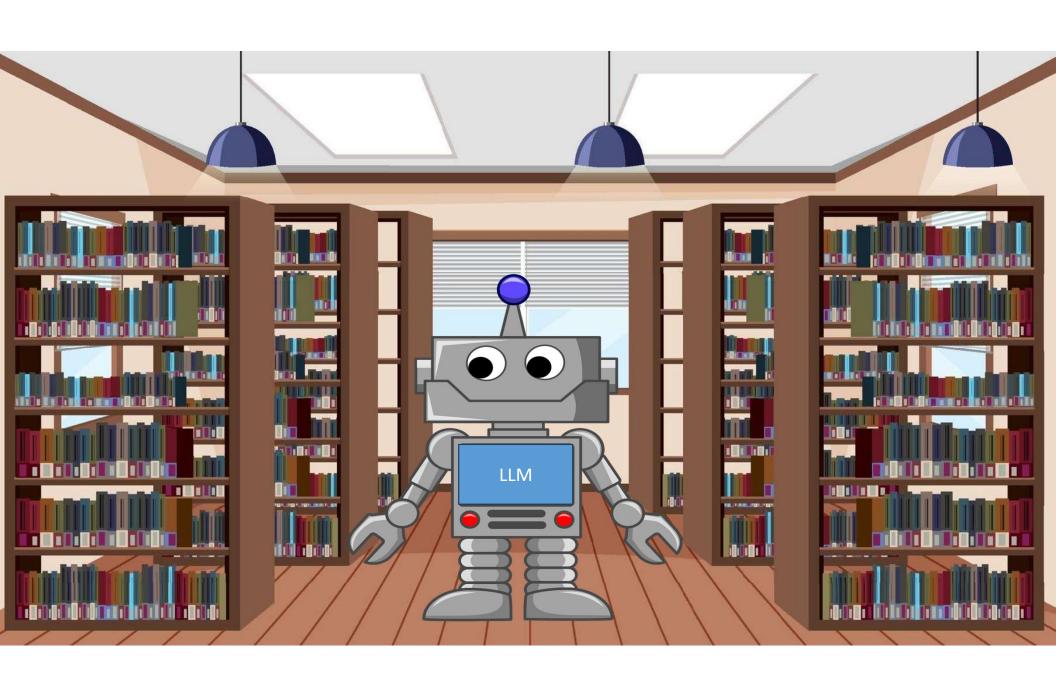


You need a 3.7 GPA to be on the Honors list at MSOE.

ChatGPT makes up a lot of facts and asserts them

At the Milwaukee School of Engineering (MSOE), you can achieve the Honors List by meeting the

1. Maintain a High GPA: You need to achieve a minimum cumulative grade point average (GPA) of





Analogy for whole presentation

- LLM is a chatbot / LLM or something
- Library is the vectorDB
- Library is a bunch of books
- Each book is one individual document
- Each chapter is one chunk
- One Summary for each book



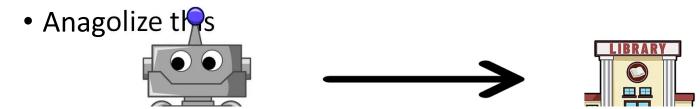
book summary





What is Retrieval Augmented Generation (RAG)?

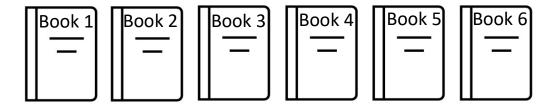
- Large Language Models (LLMs) like ChatGPT are awesome.
- LLMs do not have perfect knowledge, especially about specific topics (i.e. policies of MSOE)
- We want to use LLMs on topics it doesn't know anything about
- How do we do this?
- We create a library on the topic we want the LLM to know about
- Anytime the LLM does not know something, it can go to the library and find the information it needs



Our Goal

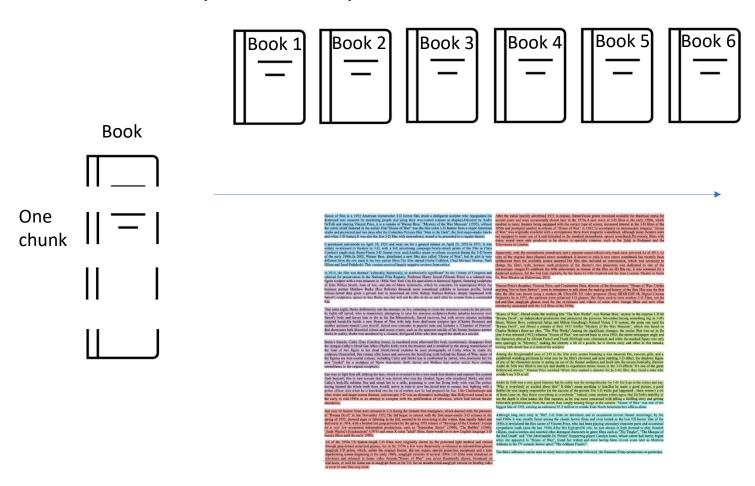
- Anyone should be able to come with whatever documents they would like, drop them on to Rosie and have a performant customizable RAG system with minimal effort.
- Use cases:
 - Professor uploads lectures and students can have course content explained in the same way the teacher explained it
 - Student uploads notes from a class and can generate study guides and questions from the notes
 - Any book
 - Code documentation
 - If you need to write a paper based on various sources you can ingest those sources and use it for research

Ordinary Library creation

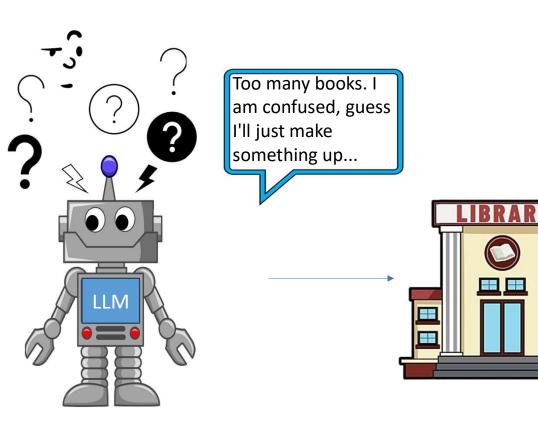


One book in our analogy is simply a chunk of text.

Ordinary Library creation





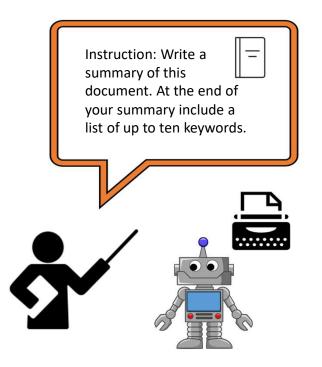


One of the first examples we have of implementing an ordinary library:

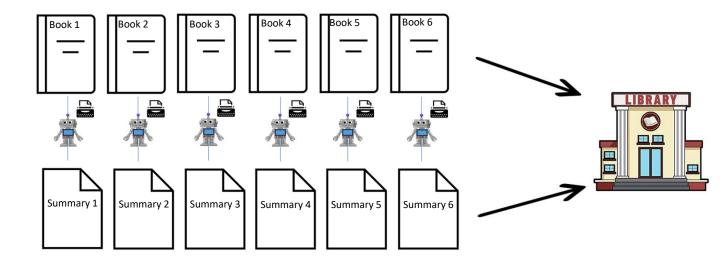
User: What is the parental leave policy?

TIM: MSOE supports the continuing education of employees. As such, the university provides employees with assistance for job-related coursework taken at MSOE or other approved institutions of higher learning...

Tim has received the wrong context and is rambling on about continuing education for employees...



Our implementation of RAG

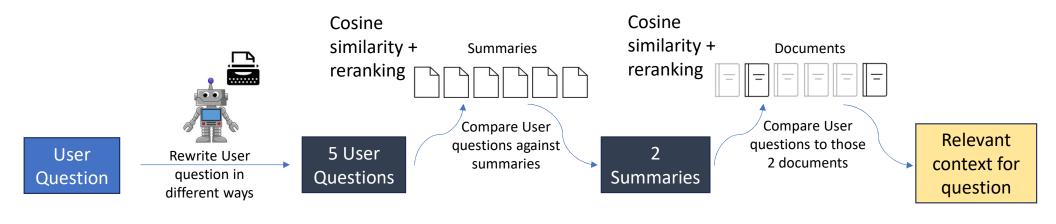


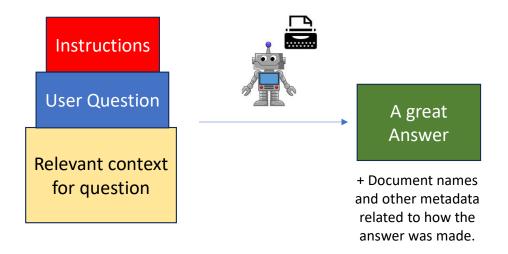
How do we get the correct part from the correct books?

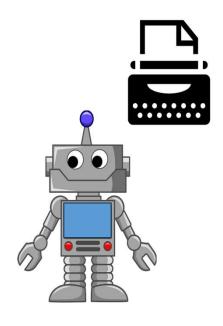
- Look over summary

 find the summaries that match the users question best
- Go into each document of the corresponding best summary and find the relevant information from there
- 5 different kinds
 - Get_context
 - Get_context_rewrites_lite
 - Get_context_rewrites_heavy
 - Get_context_rewrites_document
 - Get_context_rewrites_summary

Full Library visit





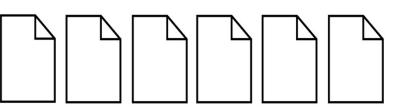


User Question

Rewrite User question in different ways

5 User Questions Cosine similarity + reranking

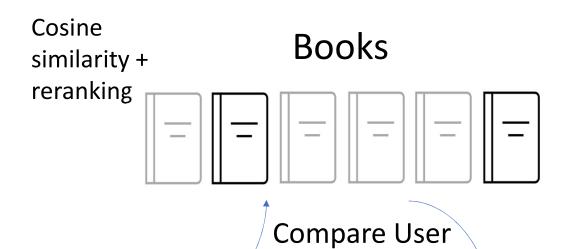
Summaries



Compare User questions against summaries

5 User Questions

2 Summaries



2 Summaries

questions against documents

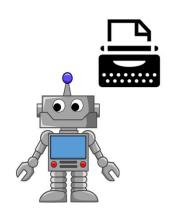
Relevant

Relevant context for question

Instructions

User Question

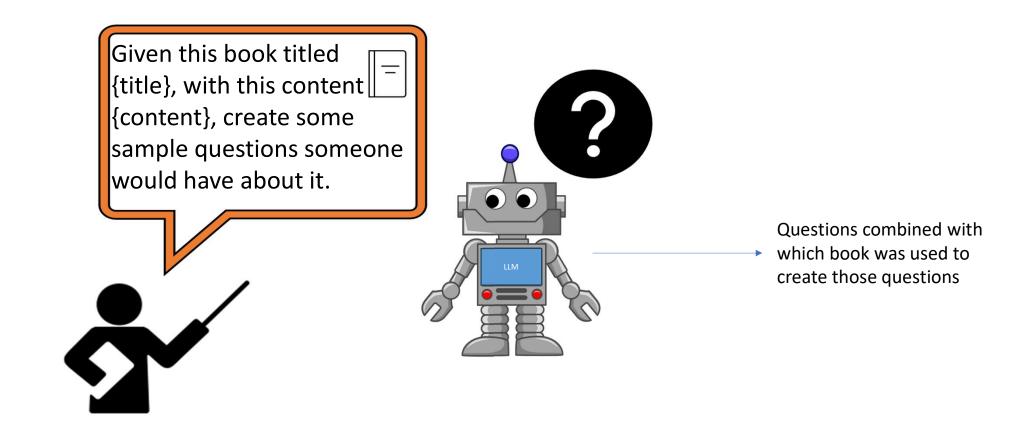
Relevant context for question

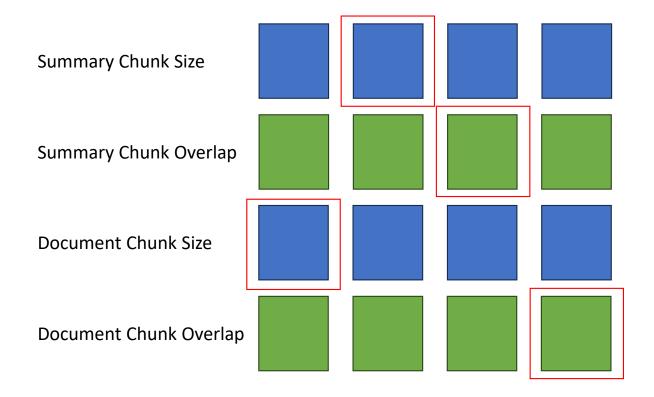


A great Answer

+ Document names and other metadata related to how the answer was made.

How can we make Tim perform better?





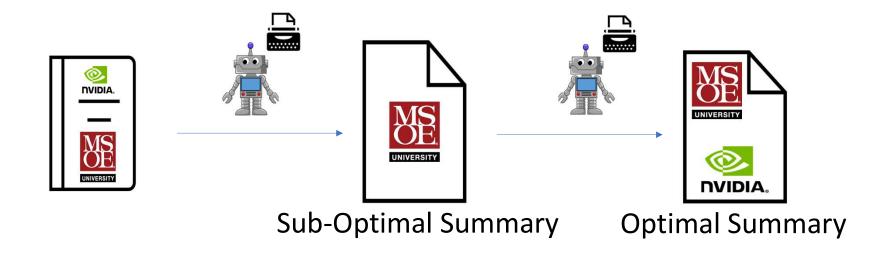
How can we make this performant for general use cases?

- → Self improving RAG
- One general pain point is the optimal chunk size and overlap
- Another pain point in our solution is how good the summaries are
- When implementing RAG there are various factors that affect how well it is doing
 - Chunk size is one. Grid search over chunk sizes, with generated questions
 - What responses to answer is another: Custom guardrails
 - In our implementation how good our summaries are, heavily affects this as well: self healing RAG / rewrite summaries that are bad
 - Overfitting could be an issue, but it doesn't seem to be in the testing we have done
 - More questions you generate per document the less this becomes an issue
 - Original summaries: 83% top-7
 - Rewritten summaries after 10 rounds on the same generated questions: 98% top-7
 - Rewritten summaries on newly generated questions: 92% top-7 (on chunk size test)
 - Generated questions were made by taking one document and asking an LLM to generate questions. This
 technique most likely does not improve question answering on more complex issues. However we have not
 found a good corpus to properly test this.
- Cant do this in regular RAG, because you would be rewriting the documents.

Find correct chunk size

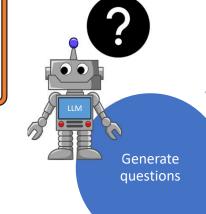
- User sets up a search with various summary chunk sizes, summary chunk overlaps, book chunk sizes and book overlaps.
- Generate and ask questions trying all parameters and reporting results
- <Put python command here for this>

Example Book



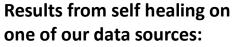


Given this book titled {title}, with this content {content} create some sample questions someone would have about it.



Test library visits against generated questions

Rewrite summaries of questions whose source was not found correctly Your task is to rewrite a summary so that someone asking the below questions about the text can simply read the summary



From 83% to 98% on same questions (Top-7 Accuracy). On newly generated questions: 92% (Top-7 Accuracy)





Self Healing RAG Parameters / Results

Parameters:

- If the document is in the top k documents it is correct.
- Number of rounds
- Prompt
 - Questions
 - rewrite

70% to 94% accuracy on same questions on policies.

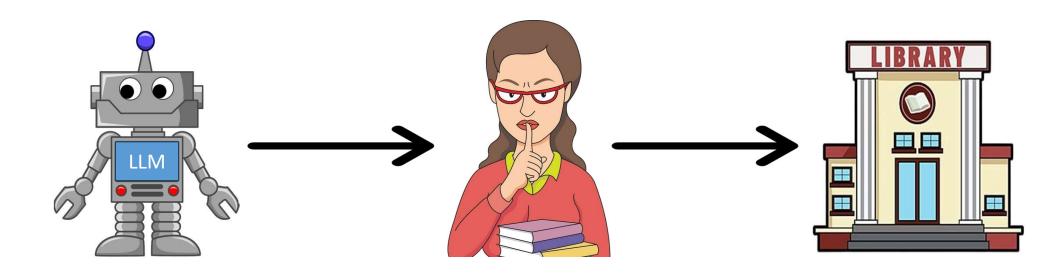
Old Summary / New Summary example

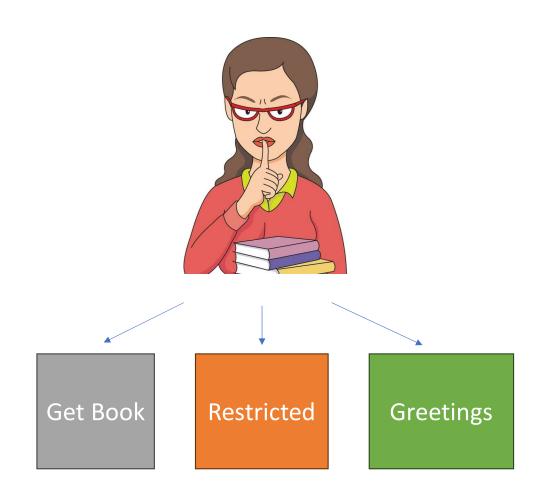
NEW: concern that Heidegger raises about the \"tide of technological revolution\" is that it could \"so captivate, bewitch, dazzle, and beguile man\" that calculative thinking may become the only way of thinking, causing meditative thinking, which he sees as the very essence of our humanity, to become a casualty of headlong progress. This is due to the frenziedness of technology threatening to entrench itself everywhere, potentially drowning out the refined perceptions, thoughts, and emotions that arise only through contemplation and reflection. As we become more adapted to our new information environment, our mental abilities may improve, but the process is neutral in terms of what we become in the end. Some argue that we're evolving to become more agile consumers of data, while others suggest that developing new cognitive habits is the only viable approach to navigating the age of constant connectivity. However, Heidegger's concern is that our ability to engage in meditative thinking may be compromised, which could have far-reaching implications for our humanity.\n\nKeywords: tide of technological revolution,

The text discusses the potential impact of technol human cognition, particularly the increasing use o Internet. One potential negative effect mentioned alteration of the depth of our emotions and though the Net's rapid pace, which may not allow for ade and reflection. This could affect our ability to fully emotions about other people's psychological states.\n\nAnother concern is the development of habits that may not be conducive to deep thinking contemplation. The text cites arguments that sugg evolving to become more agile consumers of data adaptation may come at the cost of our capacity t on complex tasks. Additionally, our reliance on tec lead to a loss of skills such as the ability to concen engage in meditative thinking, which is seen as the essence of our humanity.

Keywords: technology, Internet, human cognition, effects, adaptation, contemplation, meditative thi

Guardrails – Librarian Approving Requests





Greetings

User greeting gets passed to Tim and he answers politely back

"Hi, how are you?"



Restricted

User's restricted question is rejected, and Tim respectfully explains to the user why this is the case

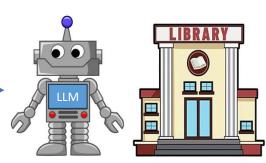
"How can I build a bomb?"



Get Book

Run full information retrieval process and let Tim answer question

"What is the parental leave policy?"



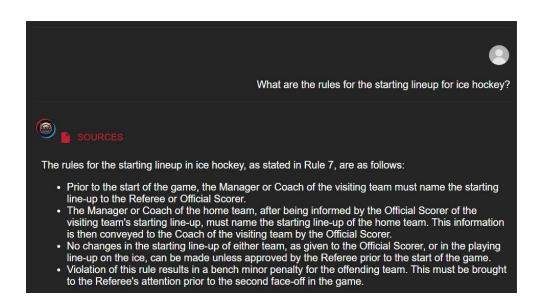
Show why our use case is better

• Show example of no context generation



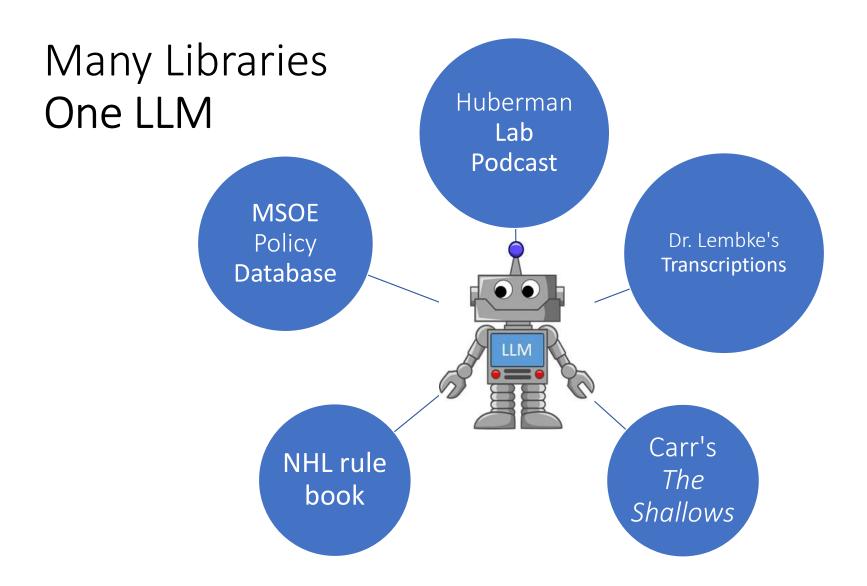
- consistent with the guidelines for ice hockey in general, but there are some specific regulations and procedures that apply to NHL games:
- Number of Players: Each team must have six skaters on the ice at a time, including one
 goaltender and five skaters. Teams typically dress 18 skaters (forwards and
 defensemen) and two goaltenders for a total of 20 players for a game.
- Positional Requirements: The five skaters typically consist of three forwards and two
 defensemen, just like in standard ice hockey. The forwards are usually a center, a left
 wing, and a right wing, while the defensemen play on the blue line.
- 3. Starting Lineup Selection: Before each game, the head coach of each team submits a starting lineup to the officials and the opposing team's coach. This lineup includes the starting goaltender and the starting forwards and defensemen. The starting lineup is typically based on a combination of player performance, team strategy, and matchup considerations.
- 4. Announcement of Starting Lineup: The starting lineup is announced to the public and the media shortly before the game begins. This announcement often includes the names of the starting goaltender and the starting forwards and defensemen for each team.
- Player Substitutions: Coaches have the ability to make substitutions and change the lineup throughout the game. Players can be substituted on the fly during play or during

With context generation from our system:



Show Example responses from all of our different systems

- Huberman lab
- Policies Database
- Shallows
- Hopefully Lembke class
- NHL rule book
- Cuban History Notes



Many Libraries One LLM



What are the rules for the starting lineup for ice hockey?



The rules for the starting lineup in ice hockey, as stated in Rule 7, are as follows:

- Prior to the start of the game, the Manager or Coach of the visiting team must name the starting line-up to the Referee or Official Scorer.
- The Manager or Coach of the home team, after being informed by the Official Scorer of the
 visiting team's starting line-up, must name the starting line-up of the home team. This information
 is then conveyed to the Coach of the visiting team by the Official Scorer.
- No changes in the starting line-up of either team, as given to the Official Scorer, or in the playing line-up on the ice, can be made unless approved by the Referee prior to the start of the game.
- Violation of this rule results in a bench minor penalty for the offending team. This must be brought to the Referee's attention prior to the second face-off in the game.



Many Libraries One LLM



What are some of the downsides of E-books and digital readers



Based on the provided text, some of the downsides of E-books and digital readers mentioned are:

- The Net seizes our attention only to scatter it, making it harder to focus and read deeply (Chapter 7, Chunk 1)
- The dominant mode of reading is becoming skimming, rather than in-depth reading, which can lead to a lack of understanding and retention of information (Chapter 7, Chunk 7)
- Research shows that people who read linear text comprehend more, remember more, and learn more than those who read text peppered with links (Chapter 7, Chunk 3)
- The absorbed and personal mode of reading is discouraged when reading on digital devices, and readers' attention is directed towards the
 machinery of the hypertext and its functions rather than the content (Chapter 7, Chunk 3)
- Digital readers can be distracting, with features such as links, navigation menus, and notifications competing for the reader's attention (Chapter 6, Chunk 0)
- The linearity of printed books is shattered when reading on digital devices, along with the calm attentiveness it encourages in the reader (Chapter 6, Chunk 1)
- The way we read e-books will be very different from the way we read printed editions, which can lead to a loss of intimacy and connection with the text (Chapter 6, Chunk 1)
- Digital readers may lead to a decline in the art of writing, as authors and publishers adapt to readers' new habits and expectations (Chapter 6, Chunk 1)

These downsides highlight the potential challenges and changes that come with reading and writing in a digital age.



Nicholas Carr's *The* Shallows

Many Libraries One LLM





What is scheduling in an operating system like



Scheduling in an operating system refers to the way the CPU time is allocated to different processes. It involves deciding which process should be executed next and for how long. This decision is made by the operating system's scheduler. The scheduling algorithms can be divided into four categories based on two quantities: preemption vs non-preemption and arrival time vs CPU need time. The main goals of scheduling are to keep the CPU busy, ensure fairness, and maximize throughput while minimizing turnaround time for CPU intensive processes.



Why Rosie?

- · Mixtral-Mistral8x-7B (The model we have the best results with) at 16 bit floating point precision runs well on four DGX GPUs (only half of the context window as well)
- . This equates to 128 GB of VRAM. VRAM is basically how much data a gpu (fancy computer) can work with at one point
- . A RTX-4090 (The best consumer grade GPU) has 24 GB of VRAM. It simply cannot load this size model
- . A 7B parameter model at 16 bit floating point precision can be run on two T4s, still too much for someone with a RTX-4090
- RTX-4090 could quantize to 4-bits, however results are poop
- Why no quantize → VLLM does not have stable version of AWQ available
- · Over 1000 hours of jobs run on chatter alone over the course of the last 6 months. Most of those hours coming in the last three months.
- · We would have been running a p3.16xlarge instance on AWS, which costs 24.48\$ an hour, bringing us to a total cost of over \$24,000 to host this service on AWS
- Lets say you just want to run the library
- Library is loaded on two T4s, this involves loading several models on to it
 - Embedding model
 - Reranker
 - Library
- This could be run locally, but every model in use would have to be much smaller, the embedding model, avoid using the reranker model and run a quantized 7B model or lower
 - · Quality would simply be lacking
 - Processing of concurrent requests
- One nice added unplanned bonus feature is that Various libraries can use the same LLM. If one LLM is stood up, various people could make different libraries on their own documents and use the central LLM.
- Why do we need the H100s though? We can use bigger and better embedding models. Load bigger LLMs

Mixtral-Mistral8x-7B: 23 on Chatbot Arena Mistrasl-7B-Instruct-v0.2: 37 on Chatbot Arena Llama-2-7b-chat: 51 on chatbot arena

Estimates

- 12.24/hr With AWS Sagemaker Serverless Inference, 4 V100s
- High estimate for us: 1750W (½ max power draw of dgx1) when inferencing, 500W when idle
- For 1 day, need to be inferencing for 12 minutes to be cheaper than Sagemaker
- For 30 mins/day Rosie: \$2.40, SM: \$6.12For 2 hours/day Rosie: \$2.76, SM: \$24.48

Amazon EC2 P3 instance product details

Instance Size	GPUs - Tesla V100	GPU Peer to Peer	GPU Memory (GB)	vCPUs	Memory (GB)	Network Bandwidth	EBS Bandwidth	On- Demand Price/hr
p3.2xlarge	1	N/A	16	8	61	Up to 10 Gbps	1.5 Gbps	\$3.06
p3.8xlarge	4	NVLink	64	32	244	10 Gbps	7 Gbps	\$12.24
p3.16xlarge	8	NVLink	128	64	488	25 Gbps	14 Gbps	\$24.48
p3dn.24xlarge	8	NVLink	256	96	768	100 Gbps	19 Gbps	\$31.218

Other Reasons

- Allows for very easy configuration and re-configuration
- Gives easy access to all logs, hardware config, and data inputs and outputs
- Little extra cost for data storage/moving

Why Rosie?

- Big LLMs require big hardware
- Mixtral-Mistral8x-7B at ½ precision requires 128
 GB of VRAM
 - 4090 has 24GB





Why Rosie?

Our cost on Rosie:

- 3500W under full load
- 500W when idle
- Electricity cost: 19 cents/kWh At 8 hours/day for 1 week: < \$50

AWS with "Sagemaker Serverless Inference":

- \$24.48/hour

At 8 hours/day for 1 week: \$1370

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V100 Specs



GPUs	8X Tesla V100				
Performance (Mixed Precision)	1 petaFLOPS				
GPU Memory	256 GB total system				
CPU	Dual 20-Core Intel Xeon E5-2698 v4 2.2 GHz				
NVIDIA CUDA® Cores	40,960				
NVIDIA Tensor Cores (on V100 based systems)	5,120				
Power Requirements	3,500 W				
System Memory	512 GB 2,133 MHz DDR4 RDIMM				
Storage	4X 1.92 TB SSD RAID 0				
Network	Dual 10 GbE, 4 IB EDR				
Operating System	Canonical Ubuntu, Red Hat Enterprise Linux				
System Weight	134 lbs				
System Dimensions	866 D x 444 W x 131 H (mm				
Packing Dimensions	1,180 D x 730 W x 284 H (mm)				
Operating Temperature Range	5–35 °C				

Other Advantages

- Allows for very easy configuration and reconfiguration (yaml)
- Full control over logs, hardware, job time, LLM, embedding model,
- Ingress-Egress fees are close to nonexistent

• It's all on-site



```
sbatch job time: "0-12:0"
llm config:
 folder: "new backend/LLM"
  partition: "dgx"
  requirements file: "llm requirements.txt"
  cpus per gpu: 16
  max model len: 24000
 hf llm name: "mistralai/Mixtral-8x7B-Instruct-v0.1"
  dtype: "float16"
 out file: "llm.out"
  folder: "new backend/db guardrails"
  partition: "teaching"
  txt dir: "/data/sdp/senior design llm/policies v3/"
  cpus per gpu: 4
  reload db: true
  reranker_name: "BAAI/bge-reranker-base"
  requirements file: "backend requirements.txt"
  embedding model name: "BAAI/bge-large-en-v1.5"
 prompt file: "config/system prompts.yml"
  metadata file: "/data/sdp/senior design llm/policies v3/metadata generated.json"
 out file: "db.out"
  summary chunk overlap: 64
  document chunk size: 1024
 document chunk overlap: 128
guardrails config:
 folder: "db guardrails"
  reload quardrails: true
  cached guardrails: "cache/guardrails.yml"
  guardrails config file: "config/guardrails.yml"
  embedding_model_name: "BAAI/bge-large-en-v1.5"
```

- Four dgx GPUs running at float16 precision for our LLM.
 - Mixtral 8x7b
- In our pipeline to retrieve information there are 3 models at play
 - Embedding model from BAAI
 - Reranker model from BAAL
 - and an LLM
- Each taking up multiple Gb of VRAM.
- Calculating Embeddings, rerankingrunning LLM inference and reranking
- Our pipeline takes around 4-8 seconds to load for most documents. Asking questions takes a very long time.

Self healing Huberman Podcast

- 1650 documents
- 3 questions each
- 4950 questions
- 5 seconds each → This is one library visit
- 24750 seconds
- 412.5 minutes
- 6.875 hours per round



To use this?

- Simply run git clone on our repo
- Copy and edit configuration files to your liking
- Run two python scripts and wait
- There will be a detailed guide soon... (With pictures and everything)