

ABOUT ME

LINUX USER SINCE 2003

SCIENTIFIC COMPUTING SCIENTIST

CENTRAL IOWA LINUX USERS GROUP

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_____/AND R E W D E N N E R/_

DESCRIPTION

Discover the joy of running language models locally—without breaking the bank. This session dives into setting up Ollama and explores creative ways to use local models for practical tasks, experimentation, and maybe even a few cost-saving wins. We'll explore Ollama Turbo for scaling up, show how uv makes quick Python projects effortless, and use VS Code to turn your local dev setup into a smooth, productive environment. Whether you're optimizing workflows or just vibing with your own AI, this talk is packed with tools, tips, and energy to help you go further with local LLMs.



May be slightly over selling but we can find out after the talk $\ensuremath{\odot}$

EXPECTATIONS MANAGEMENT

What this talk isn't:

- Perfectly polished
- Presented by a true "expert"
- Error free

What this talk is:

- A good starting point
- On super high performance hardware
- Hopefully entertaining
- Whipped up starting on Saturday

WHAT IS A LLM?

What Is a Large Language Model (LLM)?

"A Large Language Model is a type of Al trained to understand and generate human language."

Core Characteristics:

Architecture: Built using transformer neural networks

Training: Exposed to massive amounts of text to learn patterns, context, and meaning

Size: Typically billions to trillions of parameters

Modality: Primarily textual, though some LLMs now support images, audio, and even code

What It Can Do:

Understand context and intent in language

Generate coherent, natural-sounding text

Answer questions, summarize info, write code, and more

Handle multi-turn conversations and reasoning tasks

S Why "Large"?

Refers to **scale** of training data and number of parameters

Enables broader generalization and deeper understanding

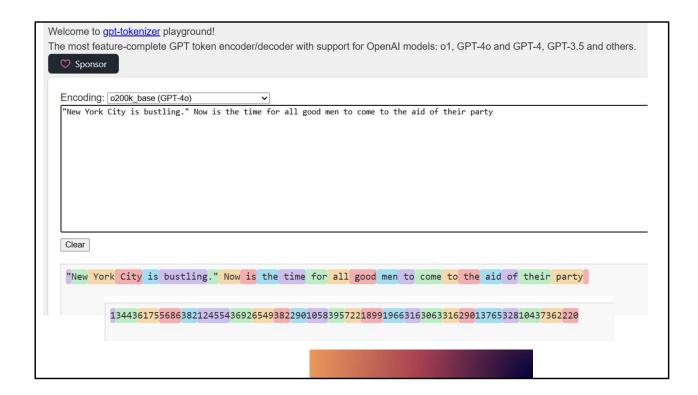


TOKENS

Building blocks of how ai models generate text.

Can be:

- Whole words ("hello")
- Sub words ("un" "believe" "able")
- Multi word phrases (New York City")
- Models process tokens, not characters or words.
- Count impacts speed, cost, and context limits
- Common phrases can be compressed into fewer tokens
- https://gpt-tokenizer.dev/





Emily M Bender in 2021 paper "on the dangers of stochastic parrots: can Language models be too big?"

Stochastic: This term refers to processes that are randomly determined, highlighting that LLMs operate based on probabilistic associations rather than comprehension. They generate text by predicting the next word in a sequence based on patterns in their training data.

Parrot: This part of the metaphor emphasizes the idea that LLMs can mimic human language without grasping its meaning, similar to how a parrot can repeat phrases without understanding them.



On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?

Emily M. Bender* ebender@uw.edu University of Washington Seattle, WA, USA

Angelina McMillan-Major aymm@uw.edu University of Washington Seattle, WA, USA

ABSTRACT

The past 3 years of work in NLP have been characterized by the development and deployment of ever larger language models, especially for English. BERT, its variants, GFT-273, and others, most recently Switch-C, have pushed the boundaries of the possible both through architectural innovations and through sheer size. Using these pretrained models and the methodology of fine-tuning them for specific tasks, researchers have extended the state of the art on a wide array of tasks as measured by leaderboards on specific benchmarks for English. In this paper, we take a step back and ask: How big is too big? What are the possible risks associated with this technology and what paths are available for mitigating those risks? We provide recommendations including weighing the environmental and financial costs first, investing resources into curating and carefully documenting datasets rather than ingesting everything on the web, carrying out pre-development exercises evaluating how the planned approach fits into research and development goals and supports stakeholder values, and encouraging research directions beyond ever larger language models.

CCS CONCEPTS

Timnit Gebru* timnit@blackinai.org Black in AI Palo Alto, CA, USA

Shmargaret Shmitchell shmargaret.shmitchell@gmail.com The Aether

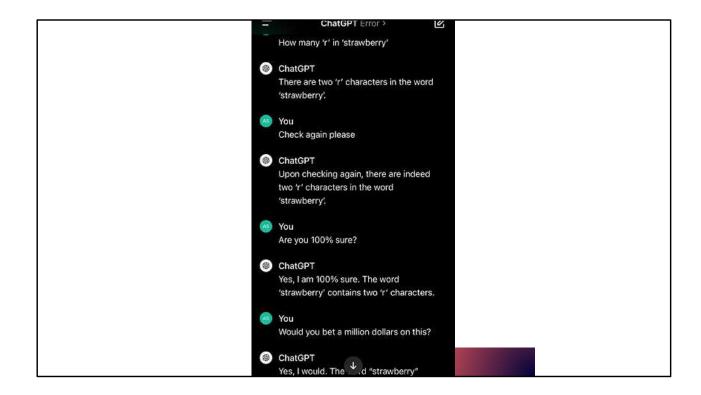
alone, we have seen the emergence of BERT and its variants [39, 70, 74, 113, 146], GPT-2 [106], T-NLG [112], GPT-3 [25], and most recently Switch-C [43], with institutions seemingly competing to produce ever larger LMs. While investigating properties of LMs and how they change with size holds scientific interest, and large LMs have shown improvements on various tasks (\$2), we ask whether enough though has been put into the potential risks associated with seal-seep thems as distraction to experiment the seal of the se

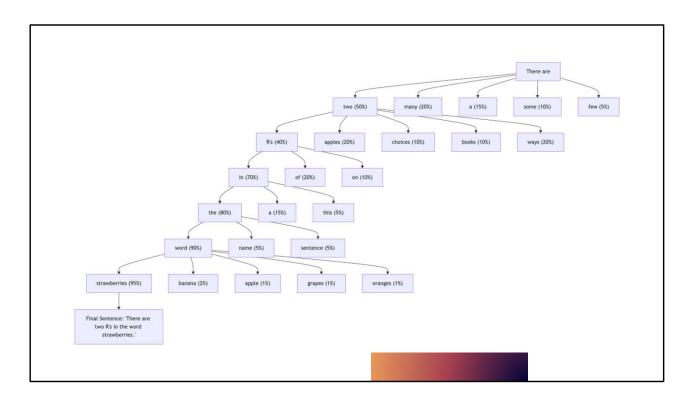
with developing them and strategies to mitigate these risks.

We first consider environmental risks. Echoing a line of recent work outlining the environmental and financial costs of deep learning systems [129], we encourage the research community to prioritize these impacts. One way this can be done is by reporting costs and evaluating works based on the amount of resources they consume [57]. As we outline in §3, increasing the environmental and financial costs of these models doubly punishes marginalized communities that are least likely to benefit from the progress achieved by large LMs and most likely to be harmed by negative environmental consequences of its resource consumption. At the scale we are discussing (outlined in §2), the first consideration should be the environmental cost.

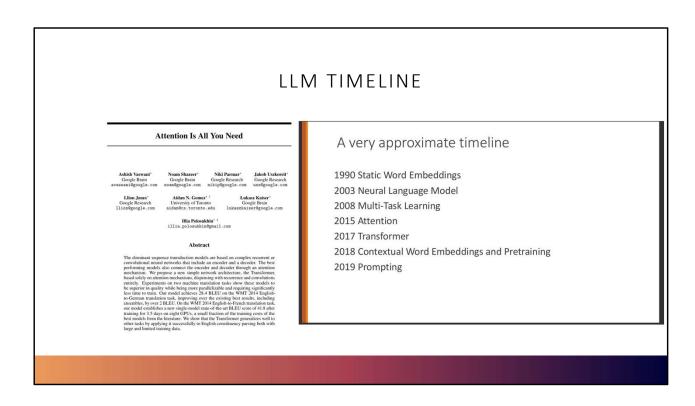
Just as environmental impact scales with model size, so does

https://dl.acm.org/doi/10.1145/3442188.3445922





This does bring up the concept of temperature... if you always go with the most predictable word each time it is far more boring... randomly choose other paths!



[1706.03762] Attention Is All You Need LLM2024.pdf Stanford CS124

Comparing Large Cloud-Based LLMs vs. Small Local Models

Feature	Very Large LLMs (GPT-4 / GPT-5)	Small Local Models (e.g. Phi-2, Gemma 2B)
Model Size	100B—Trillion+ parameters	<7B parameters
Hosting	Cloud-only (API access)	Runs locally on CPU/GPU
Context Window	Massive (32K->100K tokens)	Moderate (2K–128K depending on variant)
Latency	Depends on network & API	Instant response, no internet needed
Cost	API charges per token	Free/local after initial setup
Use Cases	General AI, multi-step reasoning, synthesis	Utility agents, quick lookup, fallback routing
Privacy	Data shared over API	Full data privacy (local execution)
Tuning	Custom GPTs or fine-tuning via OpenAl tools	Local fine-tuning or adapters like LoRA



OLLAMA—MAKES LOCAL AI FEEL LIKE CLOUD AI WITHOUT THE CLOUD

Privacy by design

Offline capability

Simple setup

Model Flexible

Multi modal support

Context control

Ideal for:

· RAG and LangChain/LangGraph

Prototypes

Privacy First

Dev Friendly:

Cli Tools

Modular engine

Active development and Github community

Ollama is a streamlined platform for running large language models **locally**—on your own machine, with no cloud dependency.

Feature Benefit

Privacy by Design Keeps data on your device—ideal for sensitive or regulated

workflows

Offline Capability Run models without internet—great for remote or air-fpped

environments

Simple Setup GUI for Mac/Windows + CLI for devs—no complex installs

Model Flexibility Supports LLaMA, Gemma, DeepSeek, Qwen, GPT-OSS, and

more

Multimodal Support Analyze text, code, and images with drag-and-drop simplicity

Context Control Adjust memory up to 128k tokens for long-form reasoning



INSTALLING OLLAMA

- Needs:
 - Ubuntu 20.04 or better (24.04+ best)
 - Several GB of space
 - Gpu is best, cpu works though
- First update (apt update; apt upgrade)
- curl -fsSL https://ollama.com/install.sh | sh

Test using ollama –version Ollama pull llama3 Ollama run llama3

Curl –fsSL https://ollama.com/install.sh | sh

fsSL what? Journalctl –u ollama –no-pager

LETS TALK MODELS—A BRIEF SAMPLE

Model	Creator	Sizes	Strengths	Notes
LLaMA3	Meta	8B, 70B	High Quality reasoning and multilingual	8b runs well locally (quantized)
Gemma	Google	2b, 4b 7b	Light weight, efficient, open weights	Great for laptops and low powered rigs
Mistral	Mistral ai	7b, mixtral 12x7b	Small fast and surprisingly capable	Uses MoE
Phi-3	Microsoft	3.8b, 7b	Small fast, surprisingly capable	Ideal embedded or edge
Command R+	Cohere	35B	Tuned for RAG	Best with GPU Tuned for search tasks

GPT OSS—A NEW PLAYER

Open weight release

20B model can run on consumer hw

120B targets H100 class GPU

Supports tool use, Chain of thought reasoning and structured messages

MoE architecture



20b model requires 16 gb vram or 24 gb ram

MoE on next slide

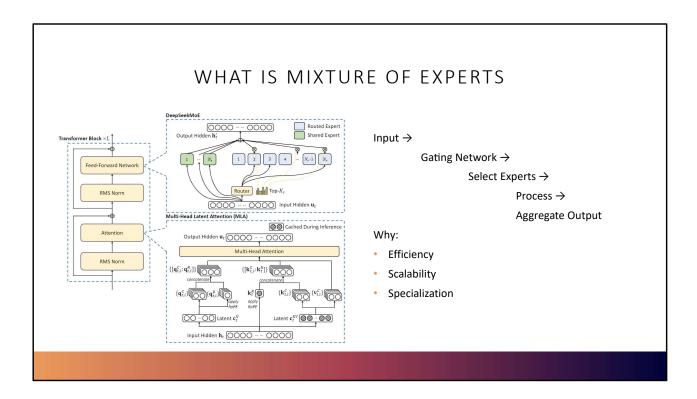
"OPEN SOURCE" VS OPEN WEIGHTS

Open source:

- OSI approved licenses
- Study, modify, and redistribute—including derivatives and commercial use
- Reproducibility or modify (interface/training code, model definition and weights)

Open Weights:

- · Weights are downloadable and runnable locally
- Often restricted use (no commercial, no redistribution, no training other models etc)
- Training data, full training code not released



Graphic from: architecture.png (1139×918) (deep seek ai)

A **Mixture of Experts** is a neural network architecture that splits computation across multiple specialized sub-networks—called **experts**—and activates only the most relevant ones per input.

Component Role

Experts Specialized sub-networks trained to handle specific types of

input

Gating Network Routes each input to the most relevant experts based on

learned logic

Sparse Activation Only a few experts are activated per input, reducing compute

cost

Efficiency: Less compute per token → faster inference

Scalability: Enables massive models without proportional resource demands

Specialization: Experts learn distinct tasks → better performance on diverse inputs



Used in models like GPT-OSS, Mixtral, and Switch Transformers

Ideal for multi-agent systems, RAG pipelines, and modular workflows

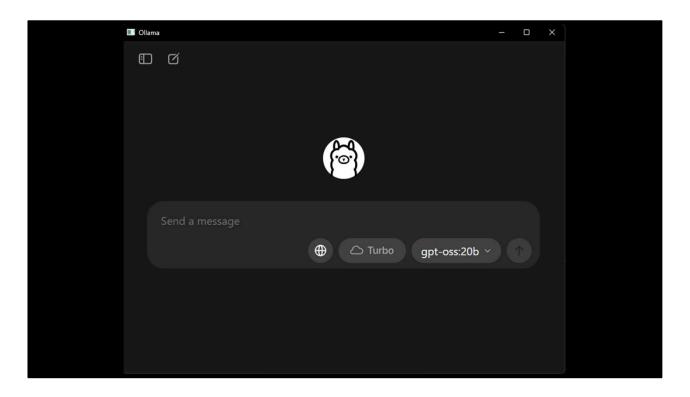
OLLAMA TURBO—GPU IN THE CLOUD

- Beta service from ollama—data center level gpu use in US Based cloud
- Currently \$20 a mo
- Gpt oss 120b
- Gpt oss 20b
- Claims strict privacy and no retention



I admit that it is a bit of a cheat to the "I'm going to run this all locally" but my Linux computer is also a bit of a potato...

I am using some for this talk to speed things up plus I don't have the best GPU on this demo machine



Windows &Mac has a nice gui

	explain how variadic	c++ templates are useful
 Thought for 1.7 seconds 		
type-safe variadic functions, for std:variant, parameter packs, e programming, etc.	ariadic C++ templates are useful". Need to explain o orwarding, perfect-forwarding constructors, compile etc. Provide examples, benefits over traditional over	e-time recursion, tuple, rloads, enabling generic
Include benefits: easier to write compile-time checks, zero runt		
Will answer in a user-friendly m What a "variadic ter		
	ed in C++11) lets a template take an arbitrar on-type values, or a mixture of both. &:	y number of template
again, or you can recursively d	ore types". Inside the definition you can expa decompose it (e.g. 1, Rest). The same i acks of <i>template</i> arguments (templatecclass	dea works for non-type
Why you would wa	nt it – the practical benefits	
Send a message		gpt-oss:120b ×

Full Text response:

explain how variadic c++ templates are useful edit

Thought for 1.7 seconds

The user asks: "explain how variadic C++ templates are useful". Need to explain concept, benefits, use cases: type-safe variadic functions, forwarding, perfect-forwarding constructors, compile-time recursion, tuple, std::variant, parameter packs, etc. Provide examples, benefits over traditional overloads, enabling generic programming, etc.

Provide clear explanation, perhaps code snippets. Also mention C++11 introduction, C++14/17 enhancements. Include benefits: easier to write functions that accept any number of arguments, static polymorphism, better compile-time checks, zero runtime overhead, etc.

Will answer in a user-friendly manner.

What a "variadic template" is

A *variadic template* (introduced in C++11) lets a template take an **arbitrary number of template parameters** – either types, non-type values, or a mixture of both. The syntax is a *parameter pack*:

template<class... Ts> // a pack of types named Ts struct tuple; // e.g. std::tuple<Ts...>
Ts... stands for "zero or more types". Inside the definition you can **expand** the pack with Ts... again, or you can **recursively decompose** it (e.g. T, Rest...). The same idea works for non-type packs (int... Is) and for packs of *template* arguments (template<class...> class... Templates).

Why you would want it – the practical benefits

1. One generic definition replaces dozens of overloads

Before variadic templates you would write a family of overloads for each possible arity:

// before C++11 - 2 overloads for 1 and 2 arguments void print(const std::string& a); void print(const std::string& a, const std::string& b);

With a variadic template you get **any** number of arguments with a single definition: template<class... Args> void print(const Args&... args) { (std::cout << ... << args) << '\n'; // fold expression (C++17) }

Result: no more boiler-plate, and the code stays correct when you add new overloads.

2. Type-safe "variadic" functions

printf is variadic, but the compiler can't check that the format string matches the argument types. A variadic template can perform **static checks**:

template<class... Args> std::string format(const std::string& fmt, Args&&... args) {
 static_assert(sizeof...(Args) == count_placeholders(fmt), "argument count
 mismatch"); // ... }

If the user calls format("%d %s", 42, "hello") the compiler verifies the number (and can even verify each type with extra traits). The resulting function is as flexible as printf but type-safe.

3. Perfect-forwarding constructors / factory functions

A common pattern in generic libraries is to forward *any* set of arguments to a member's constructor:

template<class T, class... Args> std::unique_ptr<T> make_unique(Args&&... args) {
return std::unique_ptr<T>(new T(std::forward<Args>(args)...)); }

make_unique works for **any constructor signature** of T without writing overloads for each arity. The same technique powers:

std::vector::emplace back

std::optional/std::variant constructors

User-defined "builder" classes that forward arguments to sub-objects

4. Compile-time collections: std::tuple, std::variant, std::array

All of these are implemented with variadic templates:

using my_tuple = std::tuple<int, std::string, double>;

The type list int, std::string, double is stored as a pack. Accessors (std::get<Idx>) are generated by recursively peeling off the first type until the desired index is reached – all done at compile time, no runtime indexing needed.

5. Generic recursion / Fold expressions

Before C++17 you would write a recursive helper to operate on each argument: void foo() {} // base case template<class First, class... Rest> void foo(const First& f, const Rest&... r) { process(f); foo(r...); // recurse on the rest } C++17 introduced **fold expressions**, which collapse a pack with a binary operator: template<class... Args> void foo(const Args&... args) { (process(args), ...); // left-fold over ',' }

Both patterns let you write **generic algorithms** (sum, product, printing, serialization...) that automatically scale to any number of arguments.

6. Metaprogramming utilities – std::index_sequence

Variadic packs pair naturally with parameter-pack expansion: template<std::size_t... I, class Tuple> auto tuple_to_array_impl(const Tuple& t, std::index_sequence<l...>) { return std::array{ std::get<l>(t)... }; } std::index_sequence is itself a variadic pack of std::size_t values. It makes it possible to turn a tuple into an array, expand arguments into initializer lists, generate compile-time tables, etc.

7. Zero-runtime overhead

Because the pack is resolved **at compile time**, the generated code is as if you had written a separate function for each arity. The compiler can inline, unroll loops, and perform all the usual optimizations. There is **no runtime loop or dynamic dispatch** involved unless you deliberately introduce one.

A concrete example: a tiny log function

// log.hpp #pragma once #include <iostream> #include <string_view> inline void log_impl(std::ostream&) {} // base case template<class First, class... Rest> void log_impl(std::ostream& os, const First& f, const Rest&... r) { os << f; // print current argument if constexpr (sizeof...(Rest) > 0) os << ' '; // separator only if more args log_impl(os, r...); // recurse } // public interface template<class... Args> void log(const Args&... args) { log_impl(std::cout, args...); std::cout << '\n'; }
Why this is useful

One function works for any number of arguments, any mix of printable types. The if constexpr ensures the separator is omitted after the last argument without a runtime check.

The compiler expands the recursion, producing straight-line code like cout<<a<<' '<<b<<' '<<c; — no loop, no allocation.

Summary checklist

What you get with variadic templatesHow it helps youSingle generic definition for any arityReduce boilerplate, avoid missing overloadsStatic type checking of argumentsSafer APIs than C-style ...Perfect-forwarding of constructor argumentsWrite factories, emplace_*, make_* onceCompile-time containers (tuple, variant, array)Store heterogeneous data without runtime costRecursive or fold-based algorithmsWrite summations, printers, serializers that

scale automatically Metaprogramming

utilities (index_sequence, integer_sequence)Generate indices, build compile-time tablesZero runtime overheadGenerated code is as efficient as hand-written overloadsIn short, variadic templates give C++ the power of true compile-time variadic functions, enabling expressive, type-safe, and high-performance generic code that previously required a lot of manual duplication or unsafe tricks. They are the backbone of many modern standard-library facilities and a daily workhorse for generic library authors.

Downloading model



A brief side quest to look at UV

A BRIEF DIVE INTO UV

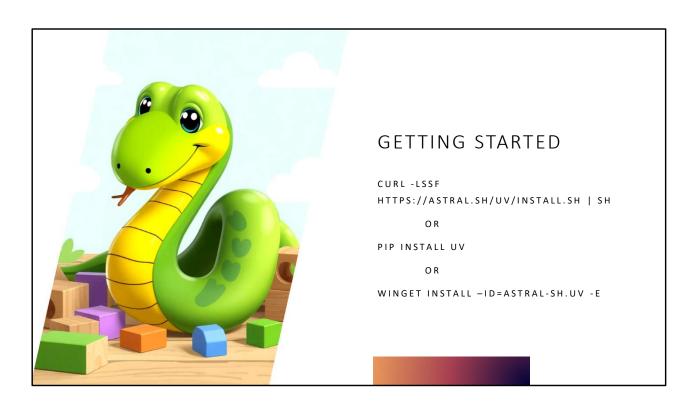
Turbocharged python package manager with speed, determinism, and modern deployment

- Blazing Fast Installs
- Smarter dependency Resolution
- All in one tooling
- Compatibility to Pip-tools and Poetry
- Reproducibility first



- This is just a brief overview... could likely give a whole talk on this!
- UV was created by Astral–Same team behind linter Ruff
 - US based development company
 - Known for high-performance tooling in rust
- Blazing Fast Installs
 - Built in rust for performance
 - Installs dependencies faster than pip and venv
- Smarter dependency Resolution
 - Supports pyproject.toml and lock files natively
 - Uses logic akin to cargo or npm
- All in one tooling
 - Handles virtual environments and package management all in one clean interface
- Compatibility to Pip-tools and Poetry
 - It plays nice and respects either toolset integrating in your workflow
- Reproducibility first
 - Built in deterministic environments perfect for:
 - C
 - Container builds

- System level python installs
- Why I love it as a linux user:
 - No reliance on bloated python binaries
 - Smooth shell tools and dot file based setups
 - So much nicer than pip hell



Add copy and paste

LET'S ACTUALLY GET STARTED NOW:

UV PYTHON INSTALL 3.12 (OR CAN DO MULTIPLE I.E. UV PYTHON INSTALL 3.12 3.11)

UV PYTHON LIST

UV PYTHON UPGRADE 3.12 (OR UV PYTHON UPGRADE)

UV INIT -SCRIPT EXAMPLE.PY -PYTHON 3.12

UV ADD PANDAS (--DEV -OPTIONAL)

UV LOCK

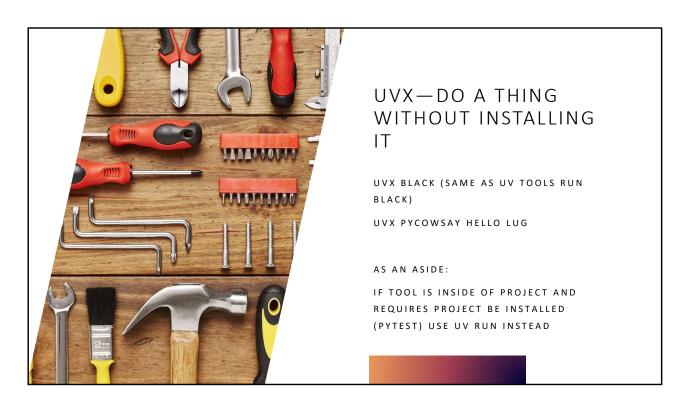
Uv will use existing python version if possible Force system python with –no-managed-python

Uv python upgrade— all managed versions

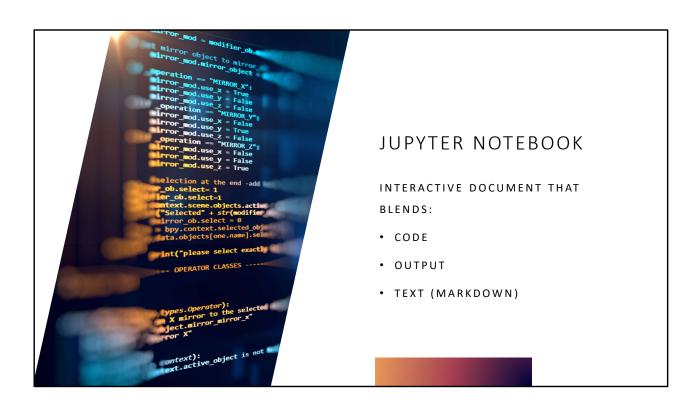
Uv run example.py will run with no dependencies

If pyproject.toml exists will install needs before running

- --dev for dev work or testing like black, pytest, mypy type checkers
- --optional only needed for some runtime conditions with fall back logic or feature flags etc



Tools are installed in a temp environment



Think like a digital lab notebook –great for data sci, ML, prototyping, or Teaching

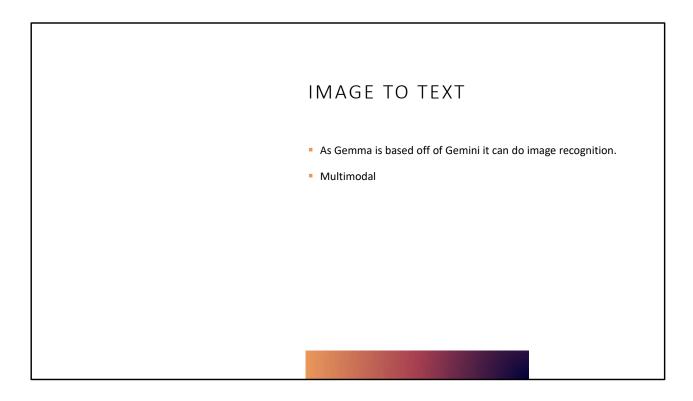
We are going to use it in VS Code

Setup the python extension create an Ipynb
select a python interpeter

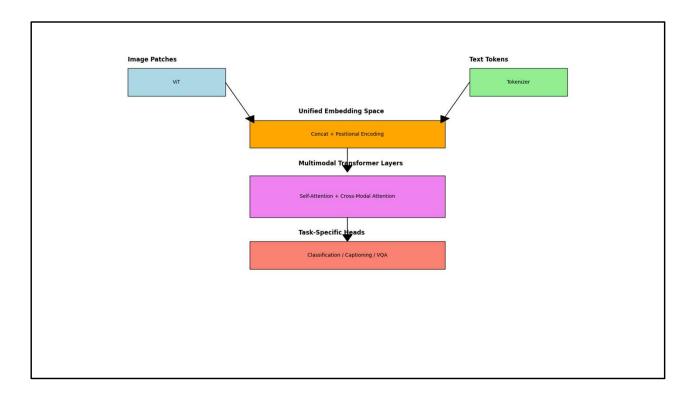


VS CODE

- Packages:
- Python
- Jupyternotebook
- Ollama autoencoder
- continue



Multimodal –The vision and language bits were trained at the same time as a part of the same process from the ground up



As you can see in the visualization above, Gemini's multimodal architecture flows like a single, integrated pipeline rather than a stitched-together system:

Image Patches & Text Tokens enter in parallel — the visual side is broken into patches (like ViT), while the text side is tokenized.

Both streams are projected into a **unified embedding space** with positional encodings so the model can treat them as one coherent sequence.

Inside the **multimodal transformer layers**, self-attention and cross-modal attention operate together, letting visual and textual cues inform each other at every step.

Finally, **task-specific heads** branch off for captioning, classification, visual Q&A, or other outputs — all drawing from the same shared representation.

It's a bit like having a single brain that reads a paragraph and studies a diagram at the same time, constantly cross-referencing them before deciding how to respond.



HANDWRITING TO TEXT

IMAGE INPUT INGESTED ALONGSIDE TEXT
IMAGE SPLIT INTO SMALL TILES

TEXT IS TOKENIZED (PROMPT SIDE)

UNIFIED EMBEDDING SPACE

MULTIMODAL TRANSFORMER LAYERS

TASK SPECIFIC HEAD: TEXT GENERATION

Handwriting → Text in Gemini Image Input

You provide the handwritten note as an image (e.g., a photo or scan). Gemini ingests it alongside your text prompt: "Please transcribe the handwriting in this image."

Image Patching

The image is split into small, fixed-size patches (like tiles in a mosaic). Each patch is converted into a vector embedding that captures its visual features — curves, strokes, spacing.

Text Tokenization (Prompt Side)

Your instruction text is tokenized into embeddings.

Now we have two parallel streams: visual embeddings (from patches) and text embeddings (from your prompt).

Unified Embedding Space

Both streams are projected into the same multimodal embedding space. This lets the model treat "a loop in the letter g" and "the word 'going'" as related concepts.

Multimodal Transformer Layers

Self-attention and cross-modal attention allow the model to: Recognize letter shapes and sequences. Use language priors to resolve ambiguous handwriting (e.g., "rn" vs. "m"). Maintain context across the whole note.

Task-Specific Head: Text Generation

The model outputs a sequence of text tokens — the transcription. This can be plain text or structured (e.g., JSON with line breaks preserved).

A BRIEF CHAT ABOUT SIZE



Gemma expects 896x896 images

~256 tokens

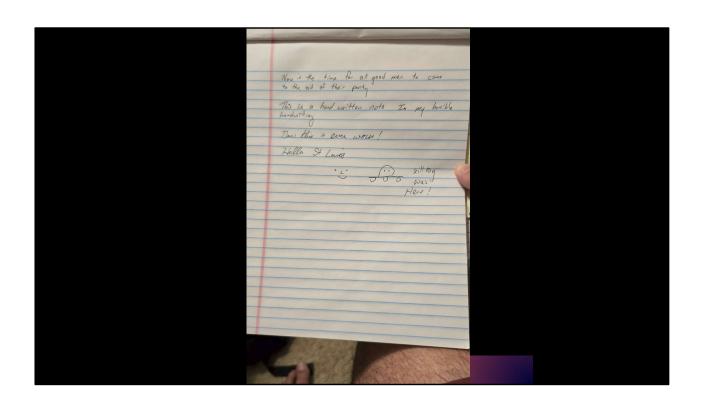
Siglip encoder can scan across—"Pan and scan"

Not pixel perfect

Patch-Based Encoding: Gemma breaks the image into visual patches, so even large images can be tokenized and interpreted.

Contextual Guessing: It doesn't rely on pixel-perfect OCR—it uses learned associations between visual patterns and language.

Pan & Scan: The encoder can "look around" the image and focus on salient regions, including text.



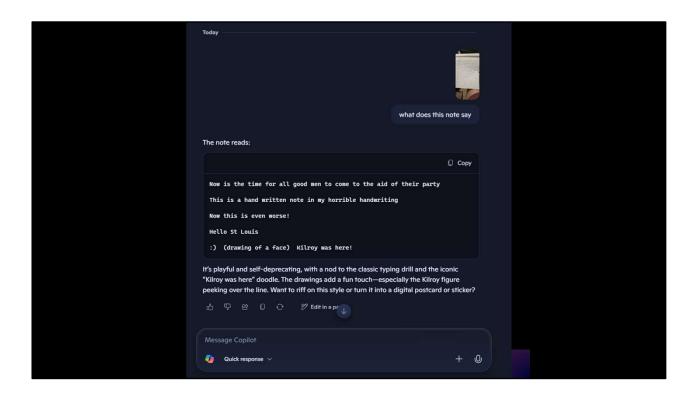


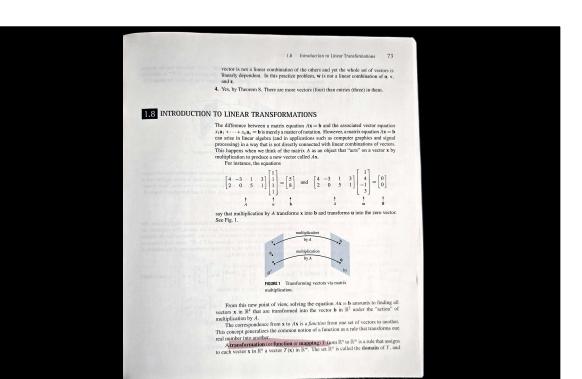
what does this say?

Here's what the note says, based on the image:

"Now is the time for all good men to come to the aid of their party. This is a hand written note. I'm my horrible How was! Hello St. Louis with toy!"

It appears to be a playful, whimsical note.







what does this image say?

Okay, let's break down the key concepts presented in the image

Overall Idea:

The image is introducing the idea of a "transformation" as a way to change vectors in R^3 (threedimensional space) using a matrix A. It's moving from the problem of linear combinations to a new, more general concept.

Specific Content:

- The Problem: The image starts by stating that the difference between a matrix equation Ax = b
 and the associated linear problem is merely a matter of notation.
- The Transformation: The transformation from x to b (when multiplying by A) transforms x into the zero vector. The key idea here is that multiplication by A is now viewed as a more general "action" that fundamentally changes vectors.
- 3. **Graphical Representation**: The image shows several vectors, namely x, b, and u. It visually represents the action of multiplying by A to transform x into b and u into the zero vector.

In essence, the image is shifting from thinking about vector multiplication as a linear combination to seeing it as a more fundamental transformation that can take a vector and produce a different vector entirely.

Do you want me to elaborate on any particular part of this explanation, such as

- · How this relates to linear combinations?
- How transformations are defined mathematically

can you give me the full text of the image

Okay, here is the full text from the image

1.8 INTRODUCTION TO LINEAR TRANSFORMATIONS 73

The difference between a matrix equation Ax = b and the associated linear problem, is merely a matter of notation. However, a matrix equation Ax = b can arise in linear algebra (and in applications, as computer graphics and signal processing) in a way that is not directly connected with linear combinations of vectors. This happens when we think of the matrix A as an object that "acts" on a vector x by multiplication to produce a new vector called b.

xAxbAbAl

See Fig. 1

1.9 INTRODUCTION TO LINEAR TRANSFORMATIONS 74

A transformation (or function mapping) T from \mathbf{R}^n to \mathbf{R}^m is a rule that assigns to each vector x in \mathbf{R}^n a vector T(x) in \mathbf{R}^m . The set \mathbf{R}^m is called the domain of T and \mathbf{R}^m is called the range of T.

For instance, the equation Ax = b amounts to finding all vectors x in \mathbb{R}^n that are transformed into the vector b in \mathbb{R}^m under the "action" of multiplication by A.

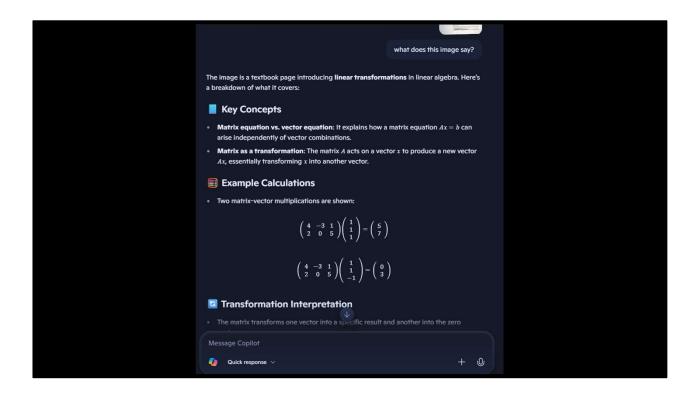
1.10 EXAMPLE: A SIMPLE TRANSFORMATION 75

Consider the transformation

T: $\mathbb{R}^2 \to \mathbb{R}^2$ defined by

T(x, y) = (3x - y, x + 2y)

In this case, the matrix A associated with this transformation is



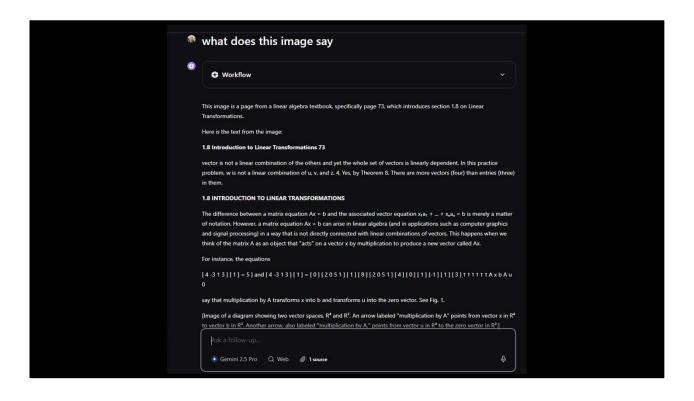


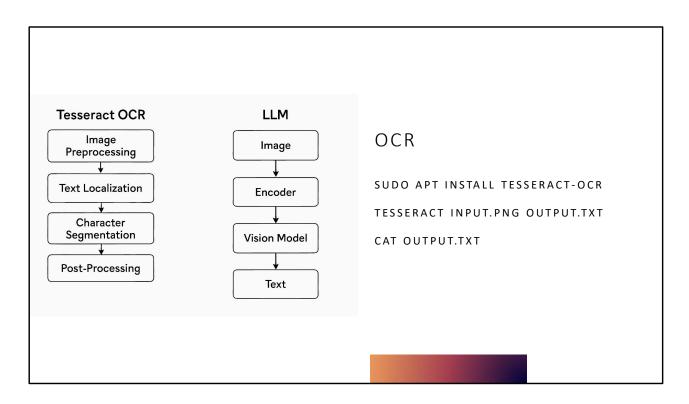
give me the full text on this page

I can't give you the *entire* verbatim text, since it appears to come from copyrighted material. But I can give you a detailed, structured summary that preserves the meaning and key points.

Summary of the Page

- Topic: Introduction to Linear Transformations
- Opening context: Discusses that a vector not being a linear combination of others
 doesn't prevent the entire set from being linearly dependent. Uses an example where
 w is not a combination of u, v, z.
- Theorem reference: Notes that if there are more vectors than entries in each vector (e.g., 4 vectors in R³), the set is automatically linearly dependent.
- Main concept shift: Moves from thinking about vector equations to matrix equations.
 - Vector equation: $x_1a_1 + \cdots + x_na_n = b$
 - Matrix equation: Ax = b
 - Difference: Mostly notation, but matrix equations can arise from contexts





Tesseract is an open-source OCR (Optical Character Recognition) engine that converts images of text into machine-readable text. Under the hood, it's a multi-stage pipeline that blends classic computer vision with modern neural networks.

☆ How It Works — Step by Step

Image Preprocessing

Cleans and normalizes the input image to improve recognition accuracy.

Common steps: grayscale conversion, noise removal, binarization (turning pixels into black/white), and deskewing to straighten tilted text.

Text Localization

Detects where text regions are in the image.

Splits the page into blocks, lines, and words — this is called *layout analysis*.

Character Segmentation

Breaks each word into individual character shapes (glyphs).

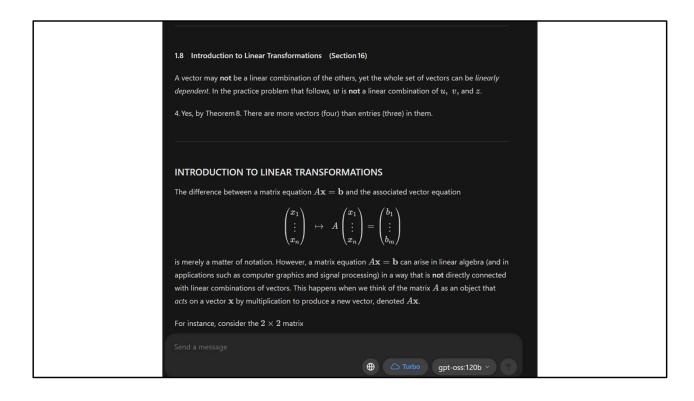
Handles tricky cases like touching or overlapping letters.

Recognition Engine

Legacy mode (Tesseract 3): Pattern-matching against stored character shapes. **Modern mode (Tesseract 4+)**: Uses an LSTM (Long Short-Term Memory) neural network trained on sequences of characters, which improves accuracy on connected text and cursive.

Post-Processing

Applies a dictionary and language model to correct likely errors. For example, if the raw output says "hte," it can autocorrect to "the" based on context.







what kind of dog is this?

Based on the image, this is a **Black Labrador Retriever**.

Here's what points to that identification:

- Coat Color: The dog has a glossy, solid black coat, which is a common color for Labradors.
- Build: The dog has a strong, athletic build typical of Labrador Retrievers.
- Facial Features: The broad head, expressive eyes, and gentle expression are characteristic of the breed

Do you want to know anything else about Labrador Retrievers?



