Generative AI and Real Estate

Gregor Schubert

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Overview of Today's Lecture

1. Review of Generative AI Capabilities
2. Use Cases of Generative AI in Real Estate
3. Building a Chatbot with Retrieval-Augmented Generation
4. How Real Estate Assets Might Change with AI

Progression of AI

Artificial Intelligence

The simulation of human intelligence processes by machines, especially computer systems.

Machine Learning

A subfield of AI focused on the use of data and algorithms in machines to imitate the way humans learn, gradually improving its performance.

Deep Learning

A machine learning technique that imitates the way humans gain certain types of knowledges; uses statistics and predictive modeling to process data and make decisions.

Generative AI

Algorithms (such as ChatGPT, Dall-E, Codex) that use prompts or existing data to create new content:

- Written: text, code
- Visual: images, videos
- Auditory: audio

Used by data scientists

AI is now accessible to all developers & users

AI vs. Generative AI

Why is “Generative AI” different?

- **pre-2022 AI & Machine Learning:** predict, classify, recommend – quality as good as your proprietary training data, customized to one use case only, only limited generalization, rigid data structure, technical knowledge needed to use
- **Generative AI / LLMs:** reason, write, explain – works with zero (additional) training data and for *all* users and has general capabilities – but work needed to customize to specific use case
  - Interprets (even unstructured) inputs, generates flexible outputs
  - Memorized (but unreliable) knowledge of facts and concepts, without external database(–> RAG)

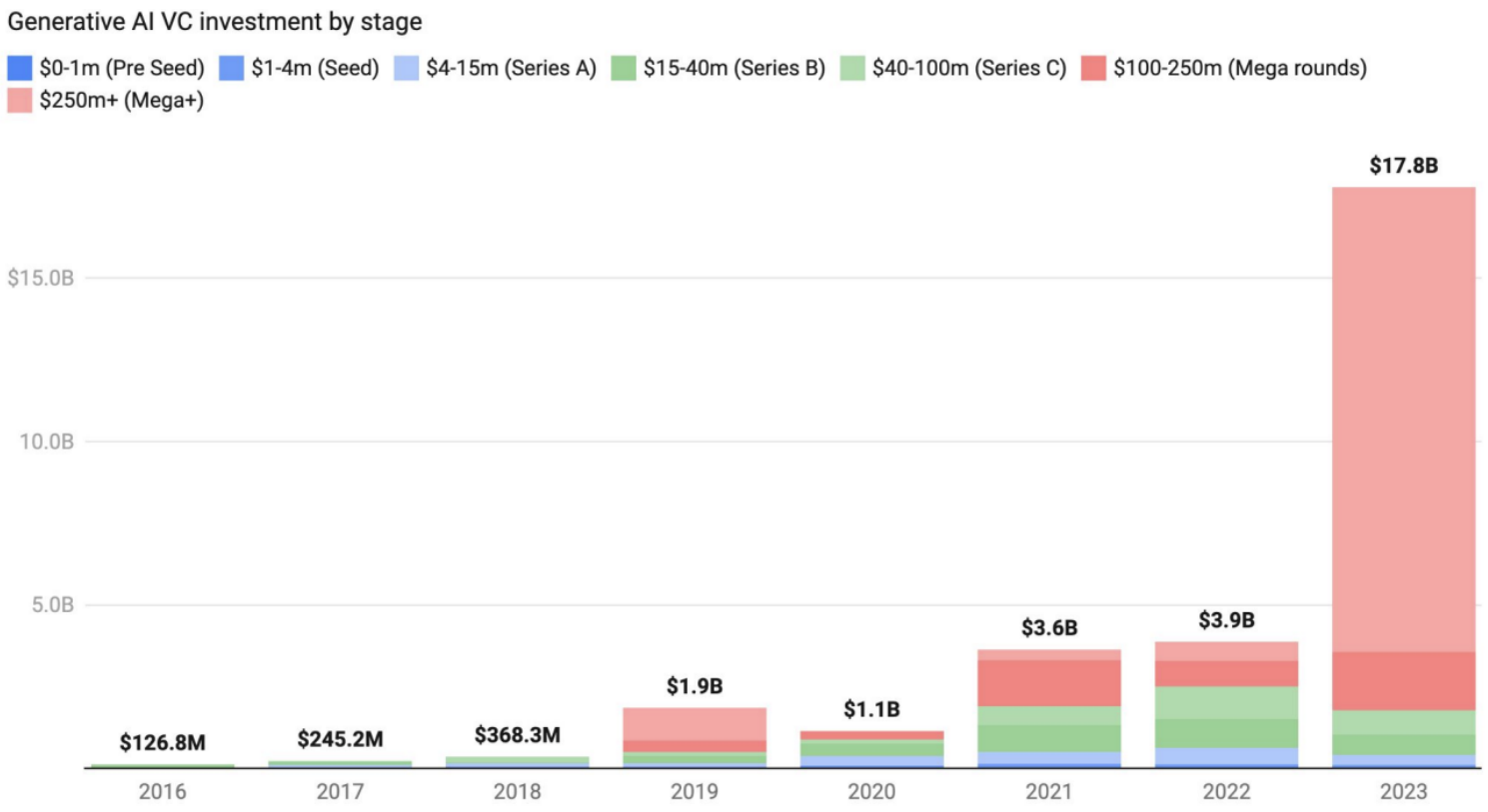
What can Generative AI do?

Generative AI comprises tools that are capable of...

- Generating text and hold conversations (Large Language Models, e.g. Generative Pre-Trained Transformers)
- Create images, movies, music based on prompts
- Take actions based on complex sensory inputs (robotics, autonomous vehicles)
- Generally understanding patterns in input data and executing tasks based on it

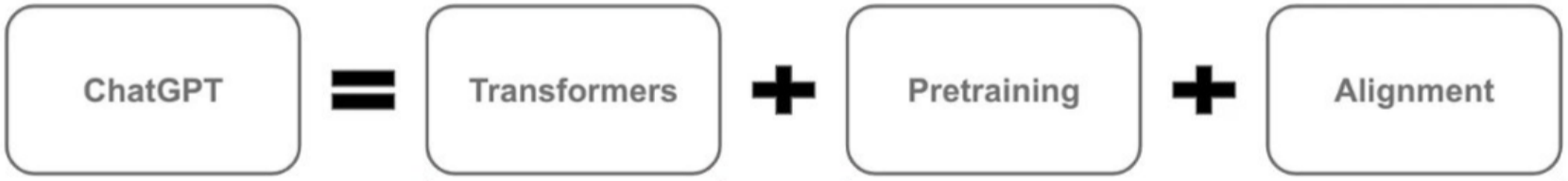
Generative AI models learn the patterns and structure of their input training data and then **generate new data** that has desired characteristics

Follow the money



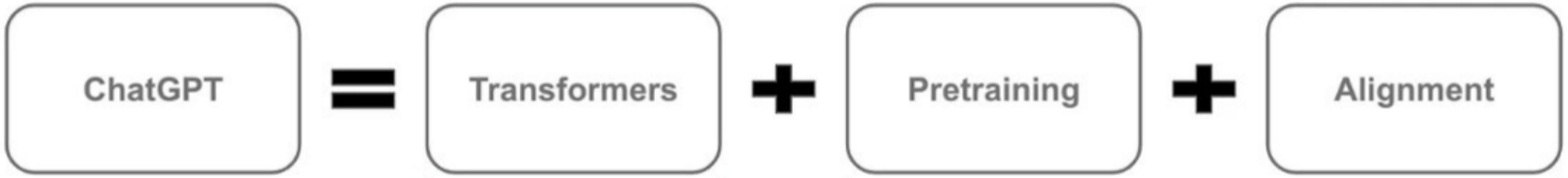
Data as of 2 Oct 2023

How do Generative AI models work?



1. **Transformers:** Language models are based upon the transformer architecture—a type of deep neural network that takes text as input. It learns meaningful relationships between words across an entire sequence of text to then produce the correct textual output in response.

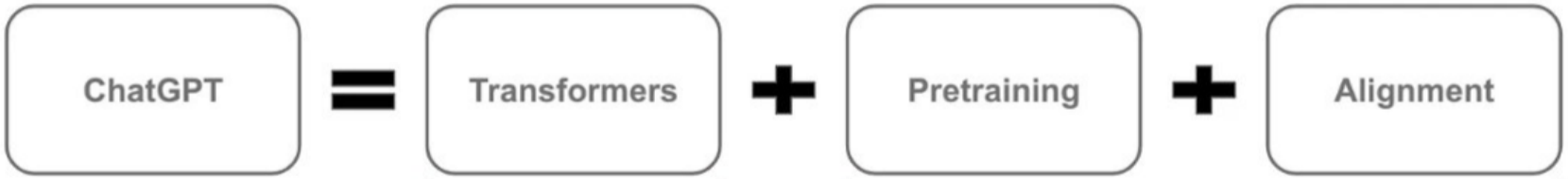
How do Generative AI models work?



2. **Pretraining:** Language models rely upon next word/token prediction objective at their core. Given a large corpus of text downloaded from the web, we just train the LLM by:
   - Sampling some text sequence from the corpus.
   - Training the model to correctly predict each word in the sequence given preceding words.

   Generation: Next word/token prediction is also used to generate text with an LLM. Starting with an input (i.e., the prompt), we just continually predict the next word.

How do Generative AI models work?



3. **Alignment:** Predicting the most likely next word is fine, but we want interesting and useful output. For this, we need to *align* the model with the desires of a human user:
   - Finetune the model on examples of desirable outputs.
   - Reinforcement Learning from Human Feedback (RLHF): finetune the model on pairs of model outputs ranked by a human annotator.

Basic LLM Workflow

What can LLMs do?

Modality	Application	Example use cases
Text	Content writing	• Marketing: creating personalized emails and posts • Talent: drafting interview questions, job descriptions
	Chatbots or assistants	• Customer service: using chatbots to boost conversion on websites
	Search	• Making more natural web search • Corporate knowledge: enhancing internal search tools
	Analysis and synthesis	• Sales: analyzing customer interactions to extract insights • Risk and legal: summarizing regulatory documents
Code	Code generation	• IT: accelerating application development and quality with automatic code recommendations
	Application prototype and design	• IT: quickly generating user interface designs
	Data set generation	• Generating synthetic data sets to improve AI models quality

What can LLMs do?

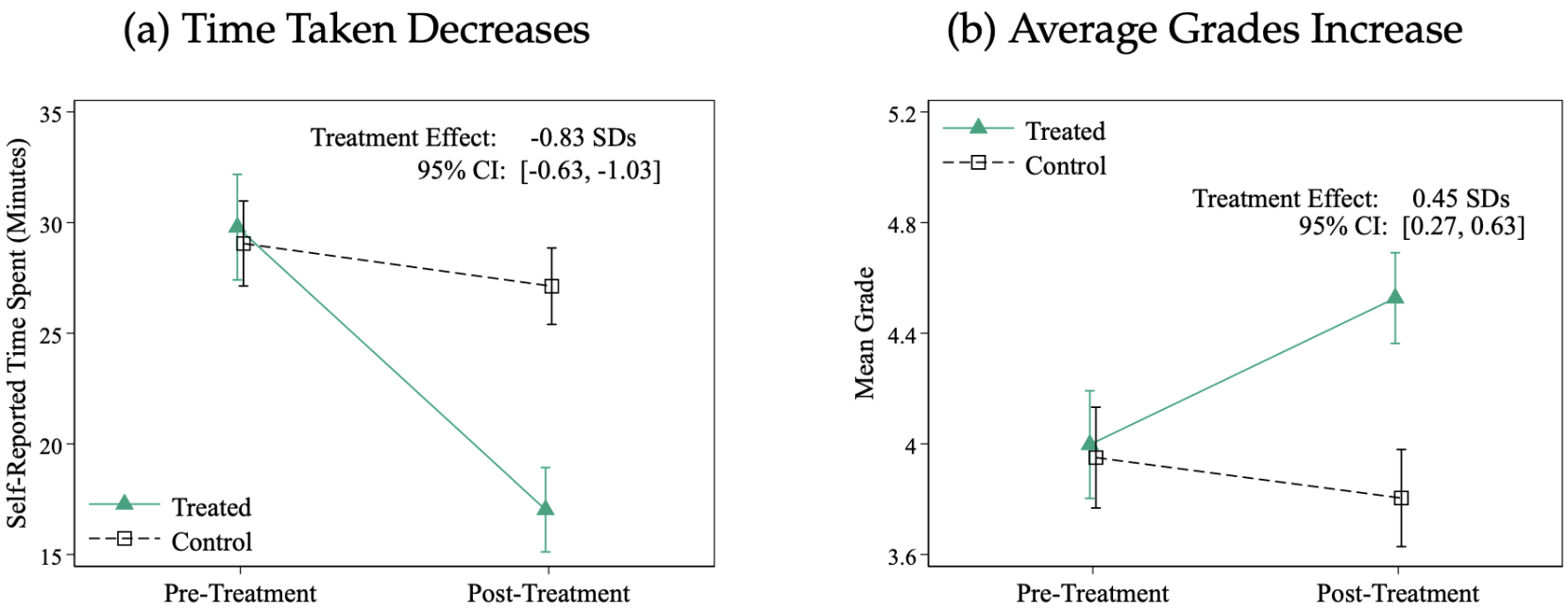
Image	Stock image generator	• Marketing and sales: generating unique media
	Image editor	• Marketing and sales: personalizing content quickly
Audio	Text to voice generation	• Trainings: creating educational voiceover
	Sound creation	• Entertainment: making custom sounds without copyright violations
	Audio editing	• Entertainment: editing podcast in post without having to rerecord
3-D or other	3-D object generation	• Video games: writing scenes, characters • Digital representation: creating interior-design mockups and virtual staging for architecture design
	Product design and discovery	• Manufacturing: optimizing material design • Drug discovery: accelerating R&D process

What can LLMs do?

Video	Video creation	• Entertainment: generating short-form videos for TikTok • Training or learning: creating video lessons or corporate presentations using AI avatars
	Video editing	• Entertainment: shortening videos for social media • E-commerce: adding personalization to generic videos • Entertainment: removing background images and background noise in post
	Voice translation and adjustments	• Video dubbing: translating into new languages using AI-generated or original-speaker voices • Live translation: for corporate meetings, video conferencing • Voice cloning: replicating actor voice or changing for studio effect such as aging
	Face swaps and adjustments	• Virtual effects: enabling rapid high-end aging; de-aging; cosmetic, wig, and prosthetic fixes • Lip syncing or “visual” dubbing in post-production: editing footage to achieve release in multiple ratings or languages • Face swapping and deep-fake visual effects • Video conferencing: real-time gaze correction

LLM Capabilities Examples

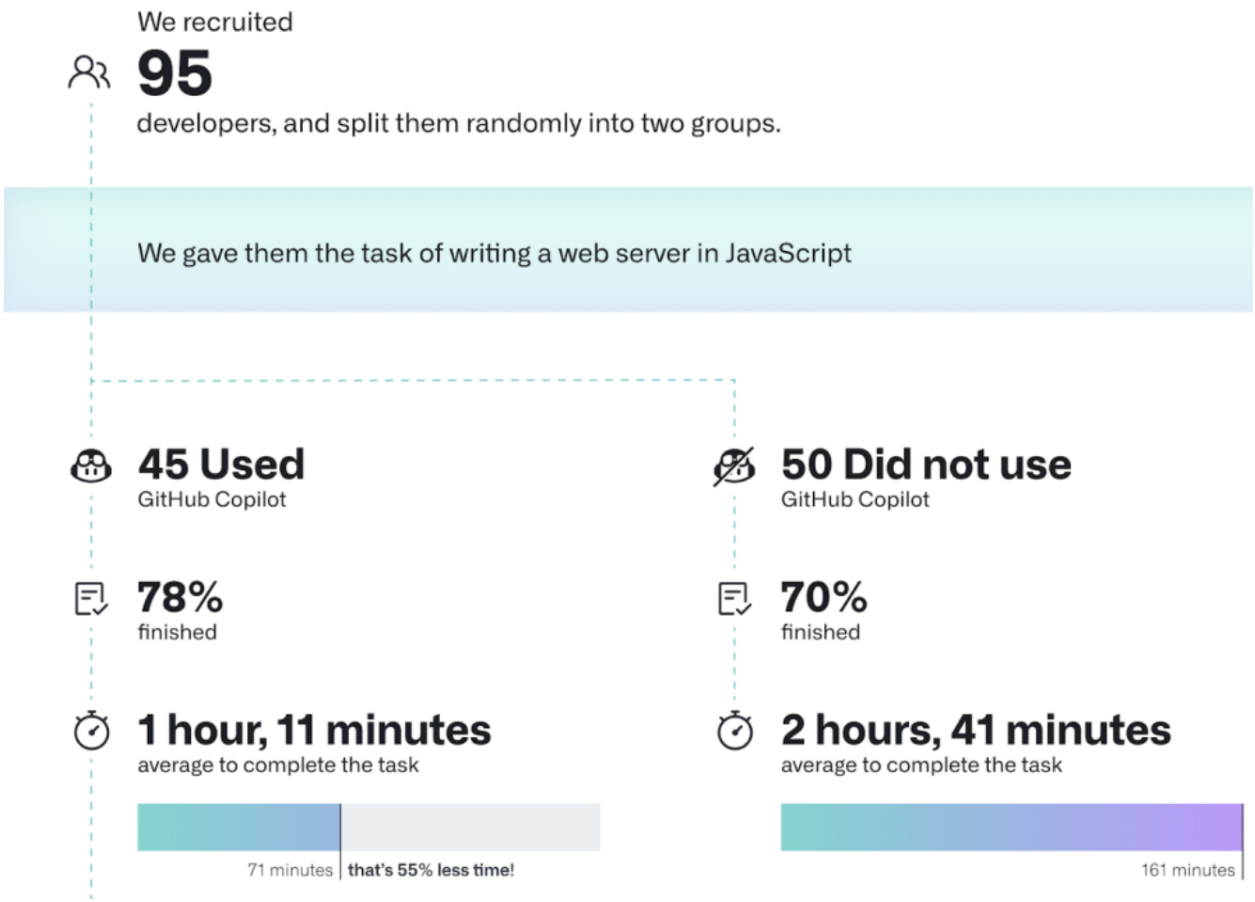
- Noy & Zhang (2023) randomize professionals into using ChatGPT when writing press releases, short reports, analysis plans, and delicate emails.



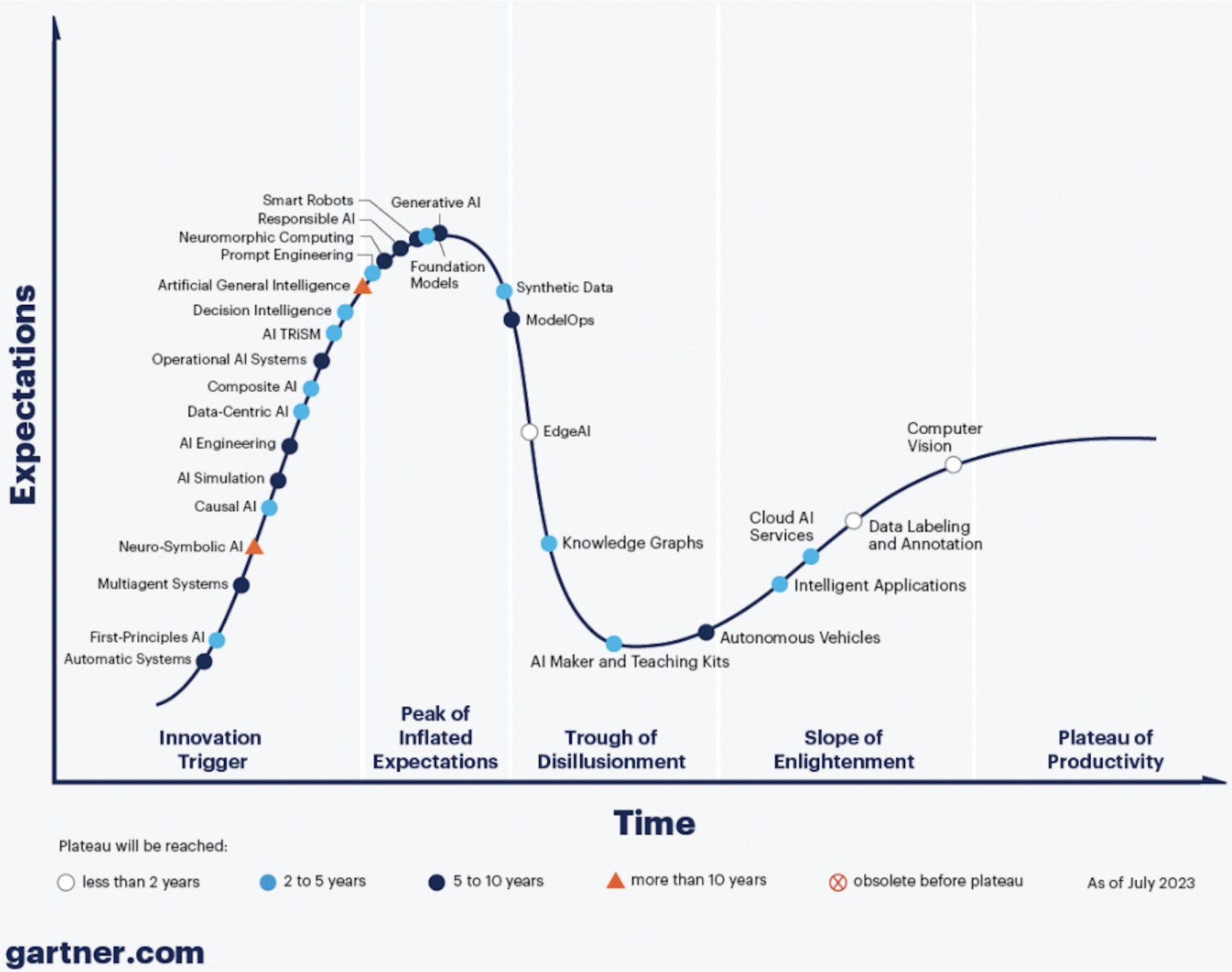
- ChatGPT access also reduced inequality and increased job satisfaction.

LLM Capabilities Examples

- Github Copilot experiment with software developers: doubled coding speed



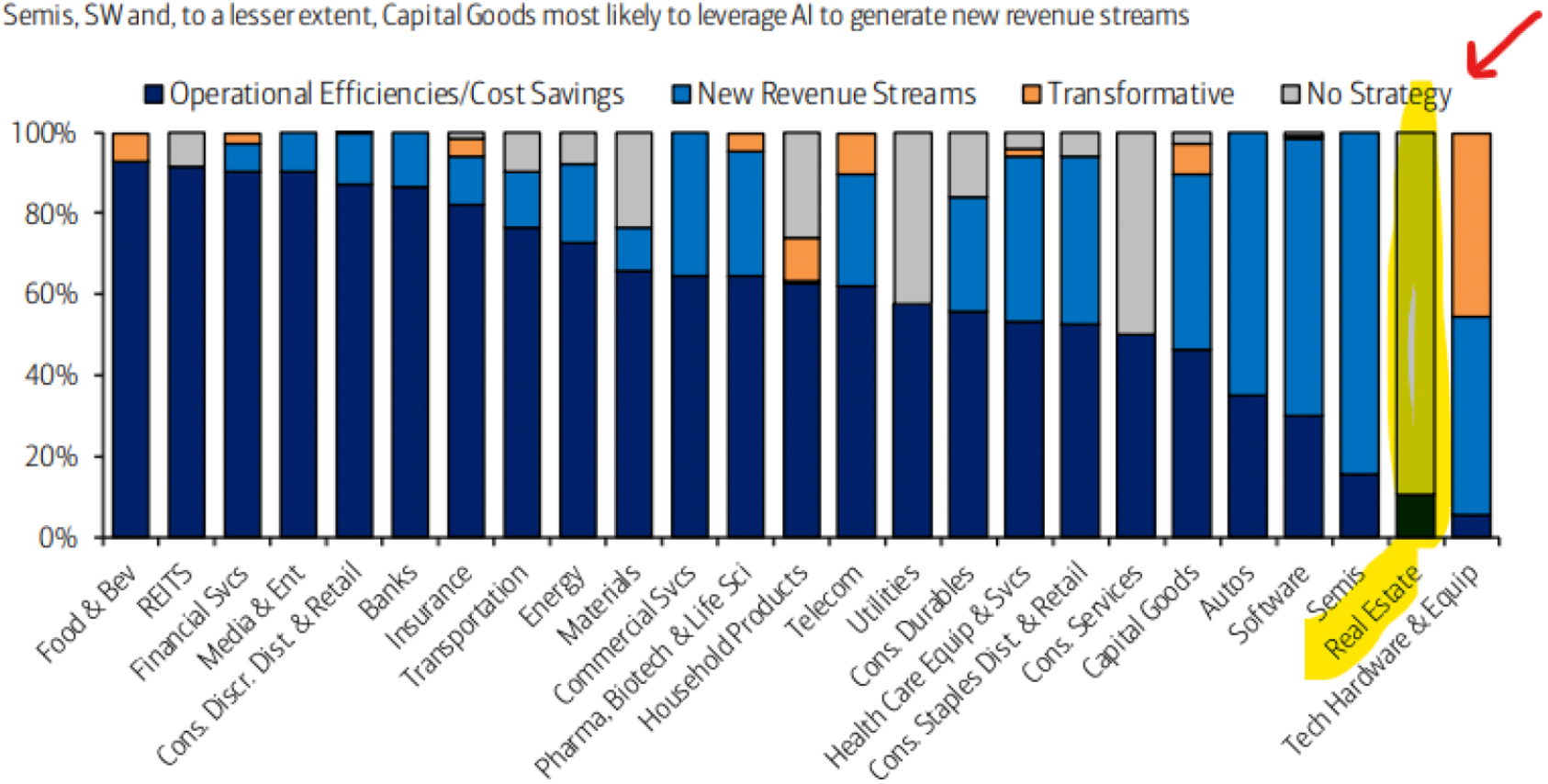
AI Hype Cycle 2023



Real Estate Needs a Generative AI Strategy

Exhibit 13: Corporate strategies to leverage AI may target new revenue streams initially but ultimately transform businesses

Semis, SW and, to a lesser extent, Capital Goods most likely to leverage AI to generate new revenue streams



Source: BofA Global Research. Results are based on survey responses.

How to develop AI use cases for your business

One approach: “BEAST”

1. **B**reak a job down into *tasks*
2. **E**valuate whether a task can be assisted by AI or automated
3. **A**ssess feasibility: value vs. cost, pre-requisites (data inputs, technical support)
4. **S**eparate out system solutions vs. point solutions: if task is automated, is the current workflow still optimal?
5. **T**ransform the organization: how do employee roles transition & what departments need to collaborate?

Task breakdown example: Real Estate Agents

Starting point: *Occupational Information Network* tasks

- **“Core” tasks: key function of the worker in the firm**
  - Generate lists of properties that are compatible with buyers’ needs and financial resources.
  - Accompany buyers during visits to and inspections of property, advising them on the suitability and value of the homes they are visiting.
  - Act as an intermediary in negotiations between buyers and sellers, generally representing one or the other.
- **“Supplemental” tasks:**
  - Contact utility companies for service hookups to clients’ property.
  - Arrange meetings between buyers and sellers when details of transactions need to be negotiated.

Feasibility assessment: “HIRES”

1. **H**igh Impact: identify tasks that are high frequency and high time / cost burden when undertaken.
2. **I**nvariance: is the workflow / process stable and can be codified? Inputs may change but what we want to do with them is similar.
3. **R**elational simplicity: how reliant is the process on inputs from few information sources with stable modes of retrieval? How many human or multi-modal interactions are required (e.g. calls, emailed information requests)?
4. **E**ase of evaluation: does the process involve expert judgment and decision-making, or complex iterative or interdependent decisions? “Could this easily be taught to an intern?”
5. **S**afety: is this process high risk or high stakes enough that quality variation is unacceptable? Do other stakeholders rely on it, leading to cascading mistakes (“O-ring processes”)?

Automatibility and work processes

Mollick (2024): task types based on *human involvement*:

1. **"Just Me" tasks:** AI not useful or not desirable.
   - May involve actions (e.g. manual work) that AIs cannot (currently) do, or which we would have ethical concerns delegating (e.g. child care)
2. **Delegated tasks:** Low-importance, time-consuming, tedious tasks that are easy for the AI
   - Requires quality controls on output
3. **Automated tasks:** AI executes without oversight.
   - Currrently small set - only low risk areas or where automated error checking (e.g. code exeuction) is possible

For *delegated tasks*, can integrate person and machine as...

- **"Centaur":** strategic division of labor, hand-offs between tasks
- **"Cyborg":** within-task back-and-forth with AI

Automatibility assessment

Eisfeldt, Schubert, Taska, Zhang (2024): determine task AI exposure based on *feasibility* of 50% productivity increase:

1. **Direct exposure:** Off-the-shelf LLM chatbot enables productivity gain for the task.
2. **Plus-overlay exposure**: Current LLMs with additional interface, data access, or connected tools enable productivity gain.
3. **No exposure**: Current LLMs cannot make this task more productive (e.g. physical tasks, face-to-face interactions).

Core vs **supplemental** task exposure: cost savings and job elimination more likely if core tasks are AI-exposed.

Task automatibility example

Eisfeldt, Schubert, Taska, Zhang (2024):

Occupation	Task	Score
Telemarketers	Adjust sales scripts to better target the needs and interests of specific individuals.	
Web Developers	Write supporting code for Web applications or Web sites.	
Paralegals and Legal Assistants	Investigate facts and law of cases and search pertinent sources, such as public records and internet sources, to determine causes of action and to prepare cases.	
Heating, Air Conditioning, and Refrigeration Mechanics and Installers	Connect heating or air conditioning equipment to fuel, water, or refrigerant source to form complete circuit.	

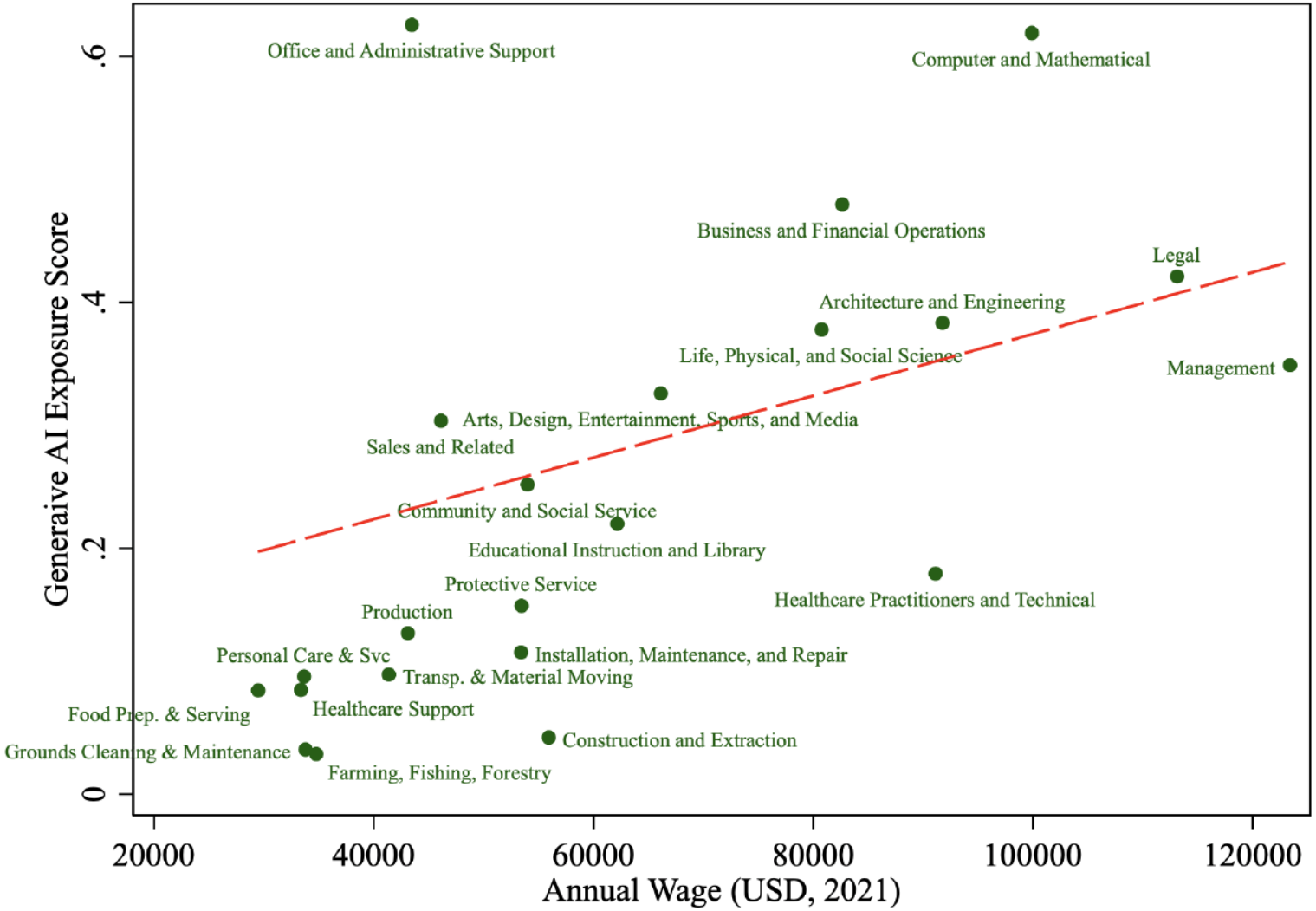
Task automatibility example

Eisfeldt, Schubert, Taska, Zhang (2024):

Occupation	Task	Score	Explanation
Telemarketers	Adjust sales scripts to better target the needs and interests of specific individuals.	1	The model can learn from the sales scripts and the needs and interests of specific individuals to adjust the sales scripts.
Web Developers	Write supporting code for Web applications or Web sites.	1	The model can write code based on the specifications provided in the text input.
Paralegals and Legal Assistants	Investigate facts and law of cases and search pertinent sources, such as public records and internet sources, to determine causes of action and to prepare cases.	.5	The model can assist in searching pertinent sources and summarizing information, but it may not be able to retrieve up-to-date facts from the internet. Additional software could be developed on top of the LLM to retrieve up-to-date facts and combine them with the LLM capabilities.
Heating, Air Conditioning, and Refrigeration Mechanics and Installers	Connect heating or air conditioning equipment to fuel, water, or refrigerant source to form complete circuit.	0	The task requires physical interaction with equipment and materials, which cannot be done by the LLM.

Generative AI exposure by occupation

Eisfeldt, Schubert, Taska, Zhang (2024):



Exercise: Generative AI Use Cases for Real Estate Agents

You're given a list of tasks for a real estate agent (Source: O*NET) and are thinking about where you can apply Generative AI:

1. Evaluate which of the real estate agent tasks AI is likely to be useful for. Select the 2-4 that you think Generative AI could most likely be a value-add for - either by assisting or automating it.
2. What is needed to make AI useful for these tasks - in terms of data, process changes, etc.?

Minimal prompt engineering rules

1. **Adding context**
   - Give the AI a role or persona (“you are a real estate agent”)
   - Provide a purpose (“you are doing cold outreach to potential buyers to schedule a call”)
   - Define an audience (“the buyers are retirees who like golf”)
   - Provide an output format by example or description (“a text message with less than 50 words”)
2. **“Few-shot” design:** give examples to work from.
   - Given a sample of what you want: *example input –> example output*
   - Provide a rubric for classification tasks (“group prospective buyers into these 5 categories:. . . ”)
3. **Chain-of-Thought:** ask the AI to go step-by-step through instructions
   - Define intermediate steps - you can also ask for explicit output of these (“first, write a marketing plan for this customer, then draft a message that represents the first step of this plan, finally adjust the wording and length to fit into a 50 word text message.”)

Prompt Engineering Example: Product Idea Generation

Meincke et al. (2024): "Prompting Diverse Ideas: Increasing AI Idea Variance"

- How does GPT-4 compare to 100 ideas generated by different MBA students?
- Task is development of new product for college students, priced under $50
- Comparison of *diversity* of ideas generated by different prompting approaches

Prompt Engineering Example: Product Idea Generation

Baseline prompt:

Generate new product ideas with the following requirements: The product will target college students in the United States. It should be a physical good, not a service or software. I'd like a product that could be sold at a retail price of less than about USD 50. The ideas are just ideas. The product need not yet exist, nor may it necessarily be clearly feasible. Number all ideas and give them a name. The name and idea are separated by a colon. Please generate 100 ideas as 100 separate paragraphs. The idea should be expressed as a paragraph of 40-80 words.

Prompt Engineering Example: Product Idea Generation

Chain-of-thought prompt:

Generate new product ideas with the following requirements: The product will target college students in the United States. It should be a physical good, not a service or software. I'd like a product that could be sold at a retail price of less than about USD 50. The ideas are just ideas. The product need not yet exist, nor may it necessarily be clearly feasible.

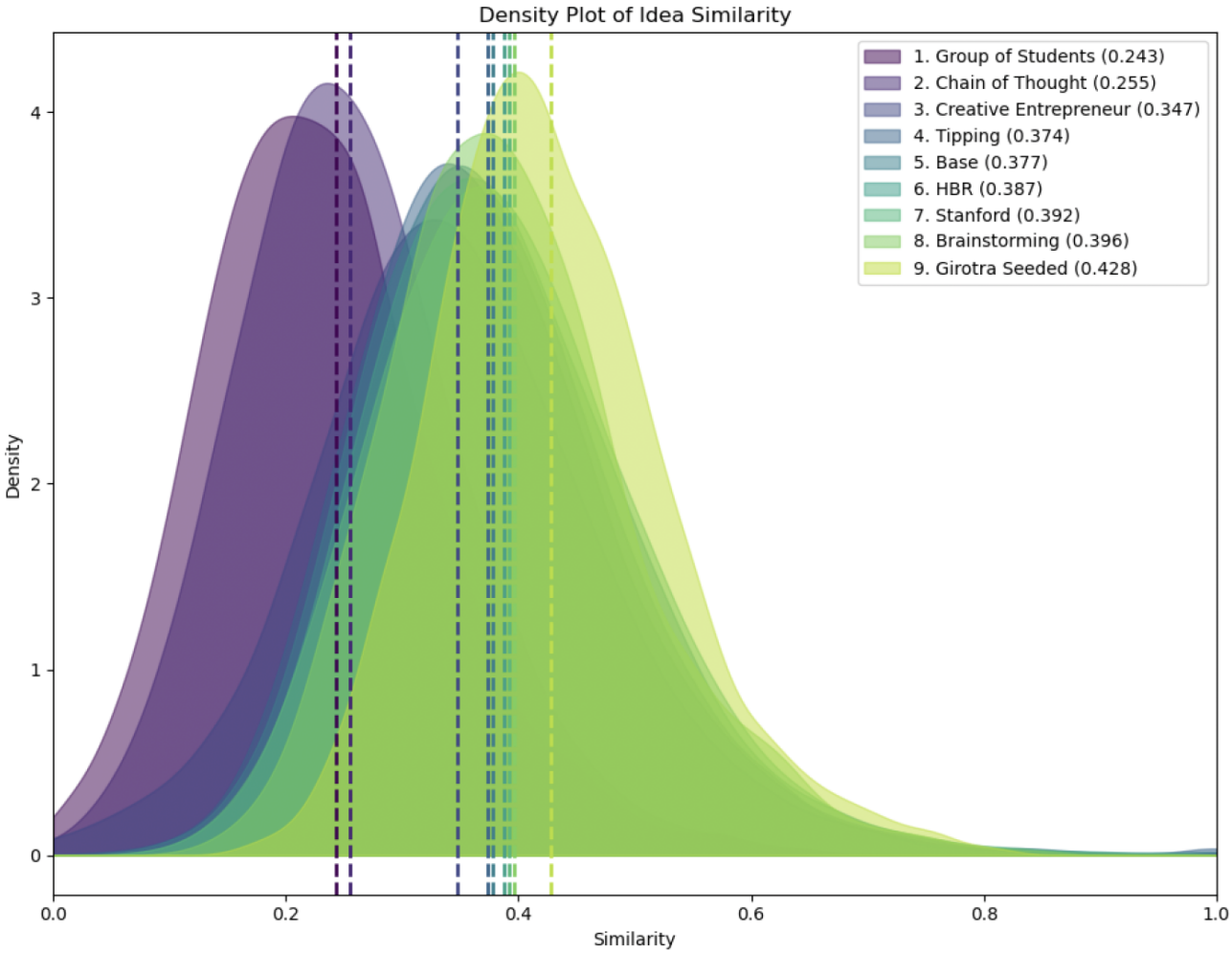
Follow these steps. Do each step, even if you think you do not need to.
First generate a list of 100 ideas (short title only)
Second, go through the list and determine whether the ideas are different and bold, modify the ideas as needed to make them bolder and more different. No two ideas should be the same. This is important!
Next, give the ideas a name and combine it with a product description. The name and idea are separated by a colon and followed by a description. The idea should be expressed as a paragraph of 40-80 words. Do this step by step!

Prompt Engineering Example: Product Idea Generation

Idea A	Idea B	Similarity
QuickHeat Mug: An insulated, battery-powered coffee mug that can heat beverages within minutes and maintain the temperature. Ideal for students who need a warm drink during long study sessions but don't have immediate access to a kitchen.	StudyBuddy Lamp: A compact, portable LED desk lamp with built-in timers for the Pomodoro study technique, adjustable brightness levels, and a USB charging port for smartphones. It's designed to help students focus and manage their study time effectively.	0.36
MiniMend Sewing Kit: A compact, travel-sized sewing kit with pre-threaded needles, buttons, and safety pins designed for quick fixes on-the-go, perfect for minor repairs or emergency adjustments to clothing.	QuickFix Clothing Repair Kit: A compact kit with needles, thread, buttons, and fabric adhesive, designed for quick clothing repairs. Ideal for students who may not have the time or skills to sew but need to fix simple clothing mishaps.	0.82

Table 1: Cosine similarity example showing pairwise similarity between ideas A and B

Prompt Engineering Example: Product Idea Generation



- Ideas generated by GPT-4 with no special prompting are less diverse than ideas generated by MBAs
- Diversity of AI generated ideas can be substantially improved using prompt engineering - especially CoT

Use Cases of Generative AI in Real Estate

1. **Prediction**
   - Predict rents and property values
   - Forecast lease renewals from payment patterns & communication
   - IoT data mining to anticipate maintenance issues
   - Incorporate qualitative data on news and trends into portfolio data analytics and benchmarking
   - Risk management using new data, e.g. satellite images
2. **Administration**
   - Responding to tenant questions and complaint
   - Maintenance request processing and forwarding
   - Rent reminders
   - Udpate listings and websites
   - Extract data from reports, offering memorandums, due diligence documentation, comparables, etc., quickly and at scale
   - Retrieve information from internal databases

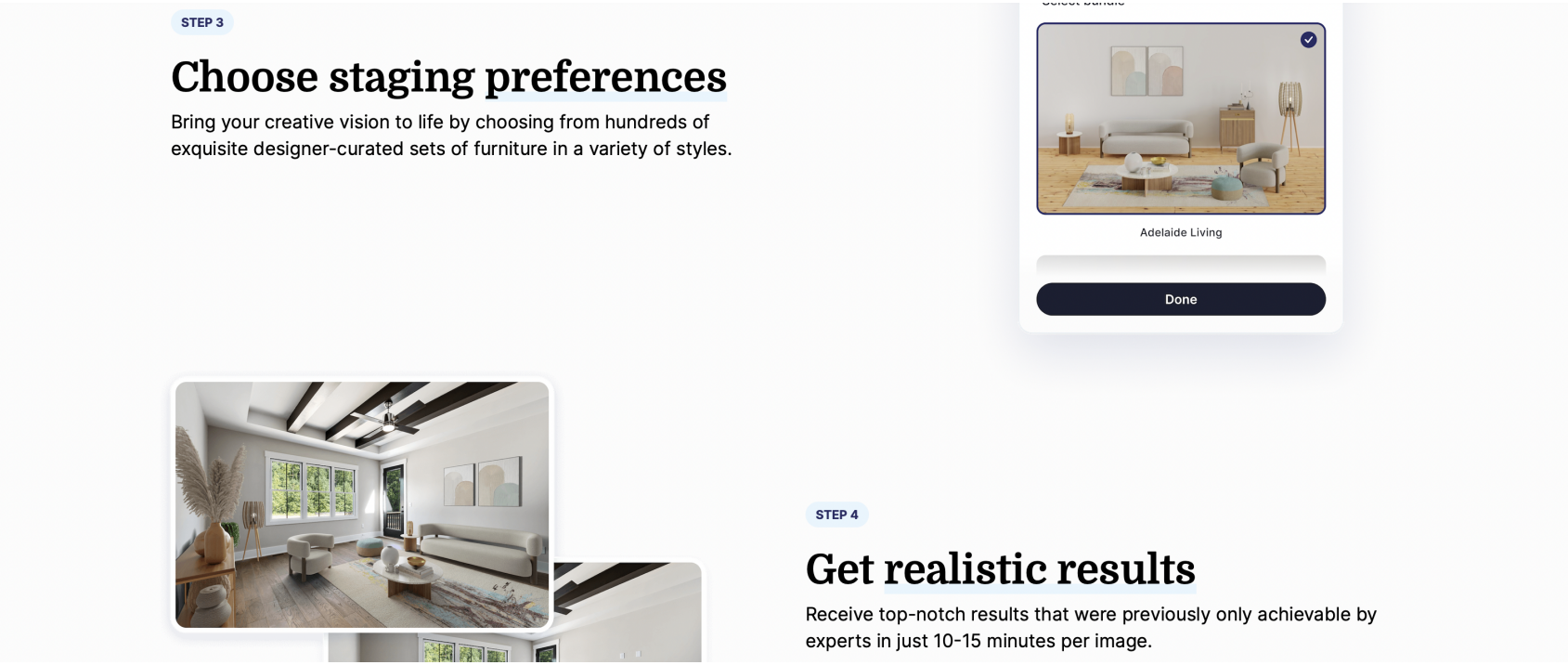
Use Cases of Generative AI in Real Estate

3. **Marketing**
   - Customization of marketing materials for prospective tenants
   - Automated directed outreach and scheduling of viewings
   - Creation and improvement of marketing assets, such as targeted social media, property descriptions, advertising copy, press releases
4. **Construction**
   - Construction site monitoring using image analysis
   - Scheduling automation and optimization
   - Augmented reality for site visits
   - Robotics and drones using AI vision and action models

...and many non-real estate specific use cases in office work!

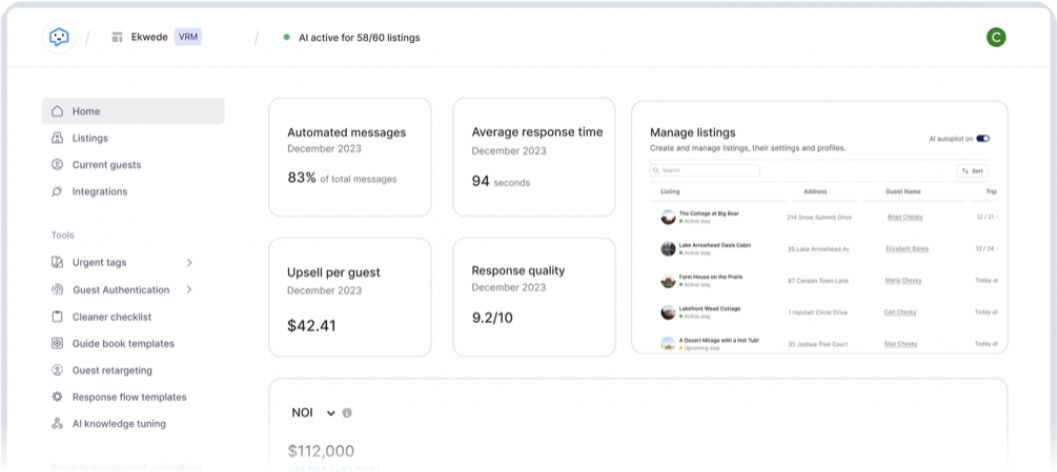
AI Proptech Examples

- **ApplyDesign.ai**: Virtual staging of homes based on property images



AI Proptech Examples

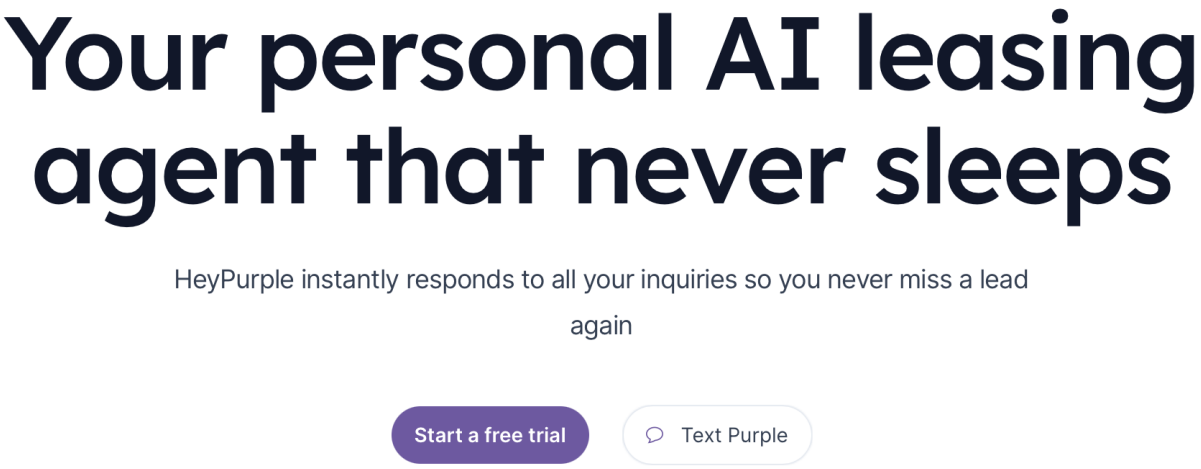
- **HostAI**: AI STR management tool kit - AI voice customer service, automatic scheduling, maintenance task generation, and calendar management

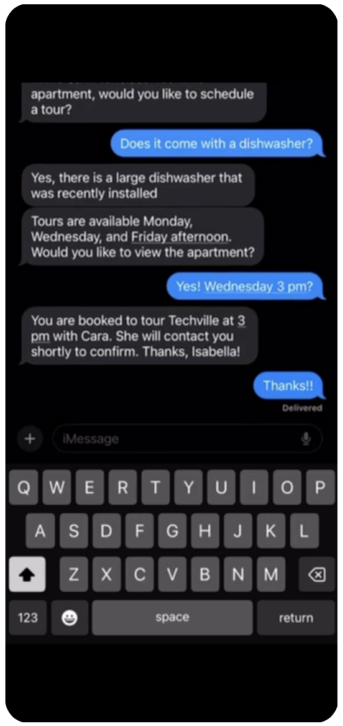


HostAI interface

AI Proptech Examples

- **heypurple**: AI leasing agent - manages prospective tenant inquiries and questions, automates tour scheduling





AI Proptech Examples

- **InspectMind**: AI inspection report drafting based on photos and voice notes from construction site.

Practical Issues in Deploying LLMs

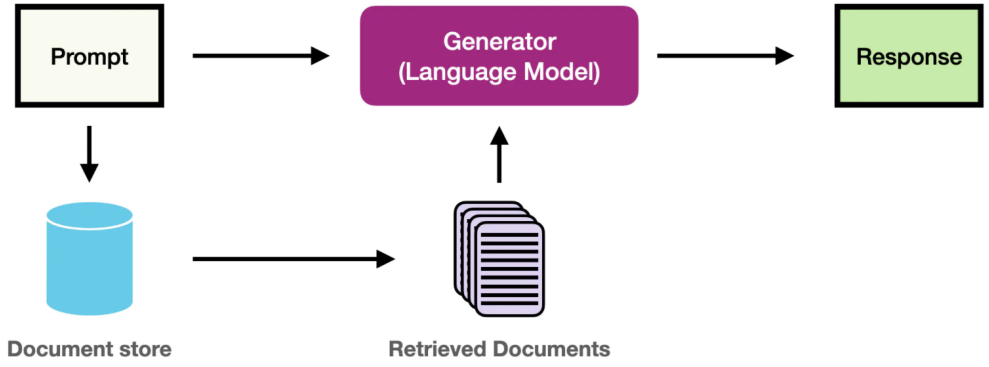
- LLMs are *not* search engines or encyclopedias
  - Work well for suggestions, brainstorming, constrained responses, verifiable output
  - Do *not* work well for factual questions or specific sources *unless* additional data and filters are added
- Management issues analogous to managing smart but inexperienced recent graduate
  - Ensure instructions are understood - risk of going off-track
  - Hallucination: models are “eager to please”, can confidently provide incorrect answers
  - Spot check and validate output for quality control
  - Break complex tasks down into steps
  - Templates and examples are helpful
  - Do not delegate final say or output - use for first drafts and then polish yourself
- Ethical issues: is this just *replacing* workers?
  - Autor (2024): “like Youtube for plumbers” – allows you to go deeper and leverage foundational skills across domains

RAG: Retrieval-Augmented Generation

Basic LLM use case: [Prompt] –> [Response]

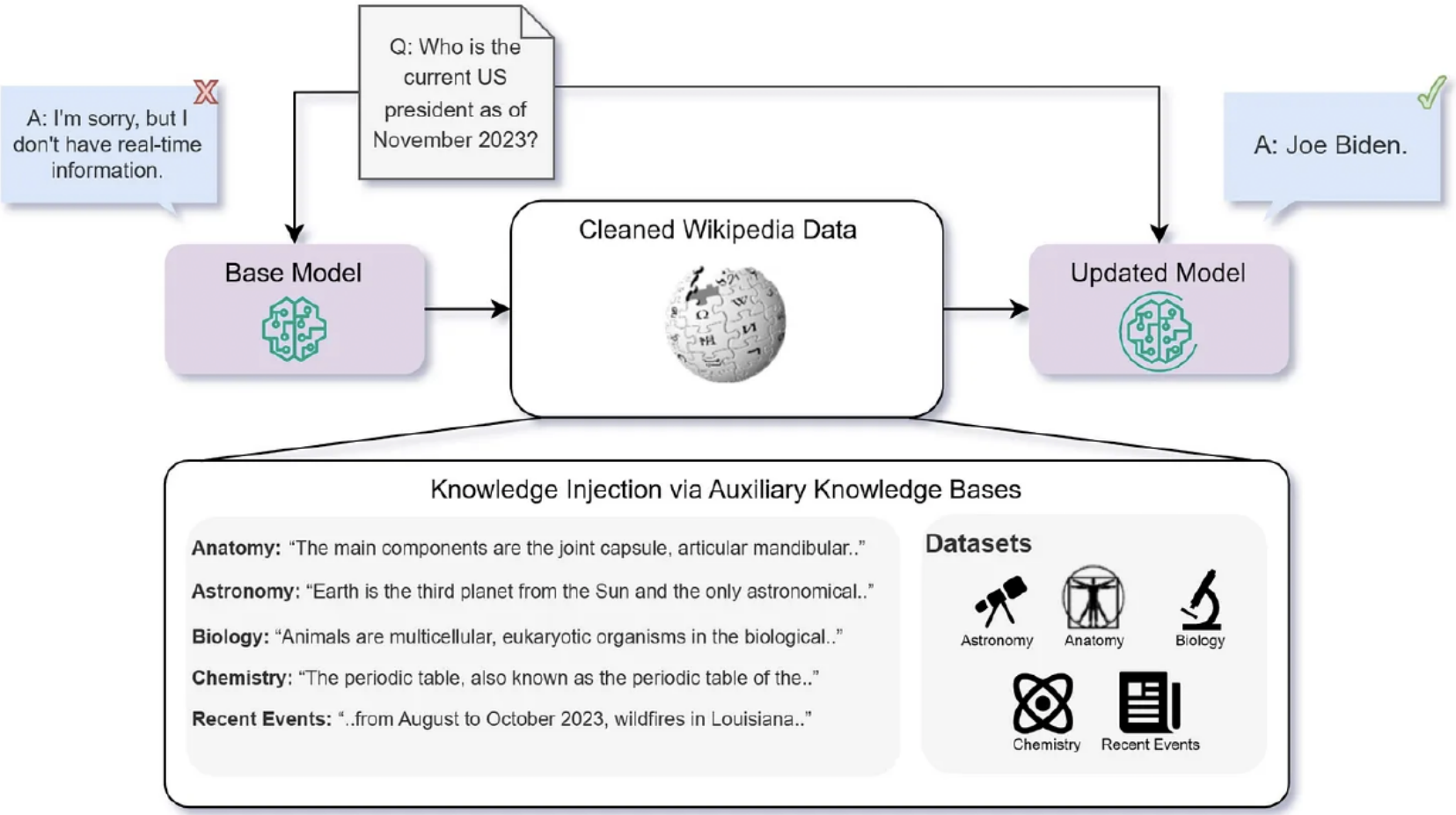
- Uses baseline capabilities of the LLM “out-of-the-box”
- No customization to related information

RAG:



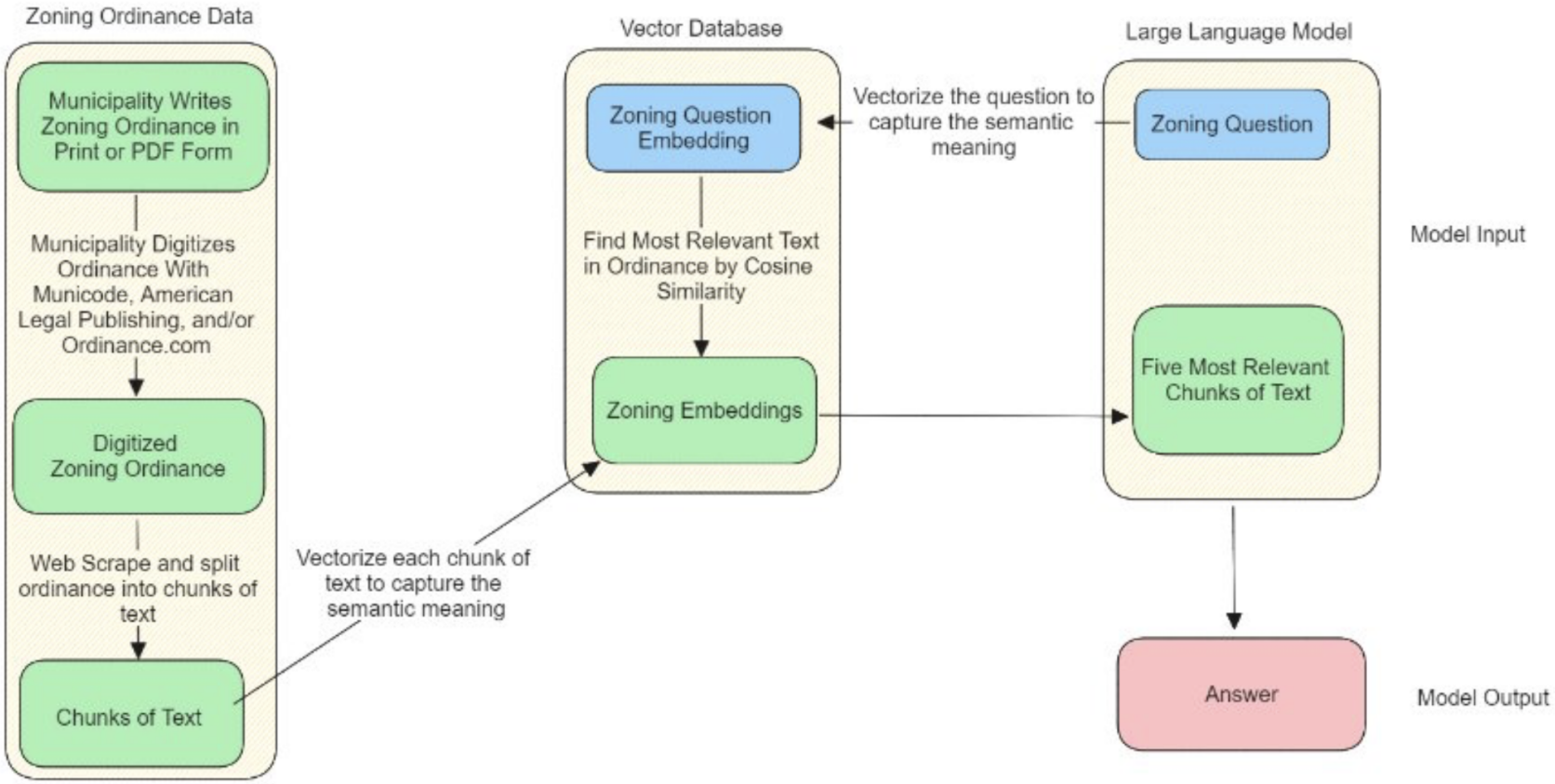
- Provide LLMs with “knowledge injection” *retrieved* from a reference textual database
- Computationally cheaper than alternatives, e.g. fine-tuning

RAG example: adding Wikipedia information into a query



RAG example: automated zoning measurement

Bartik, Gupta, Milo (2023) - “The Cost of Housing Regulation: Evidence from Generative Regulatory Measurement”



RAG example: automated zoning measurement

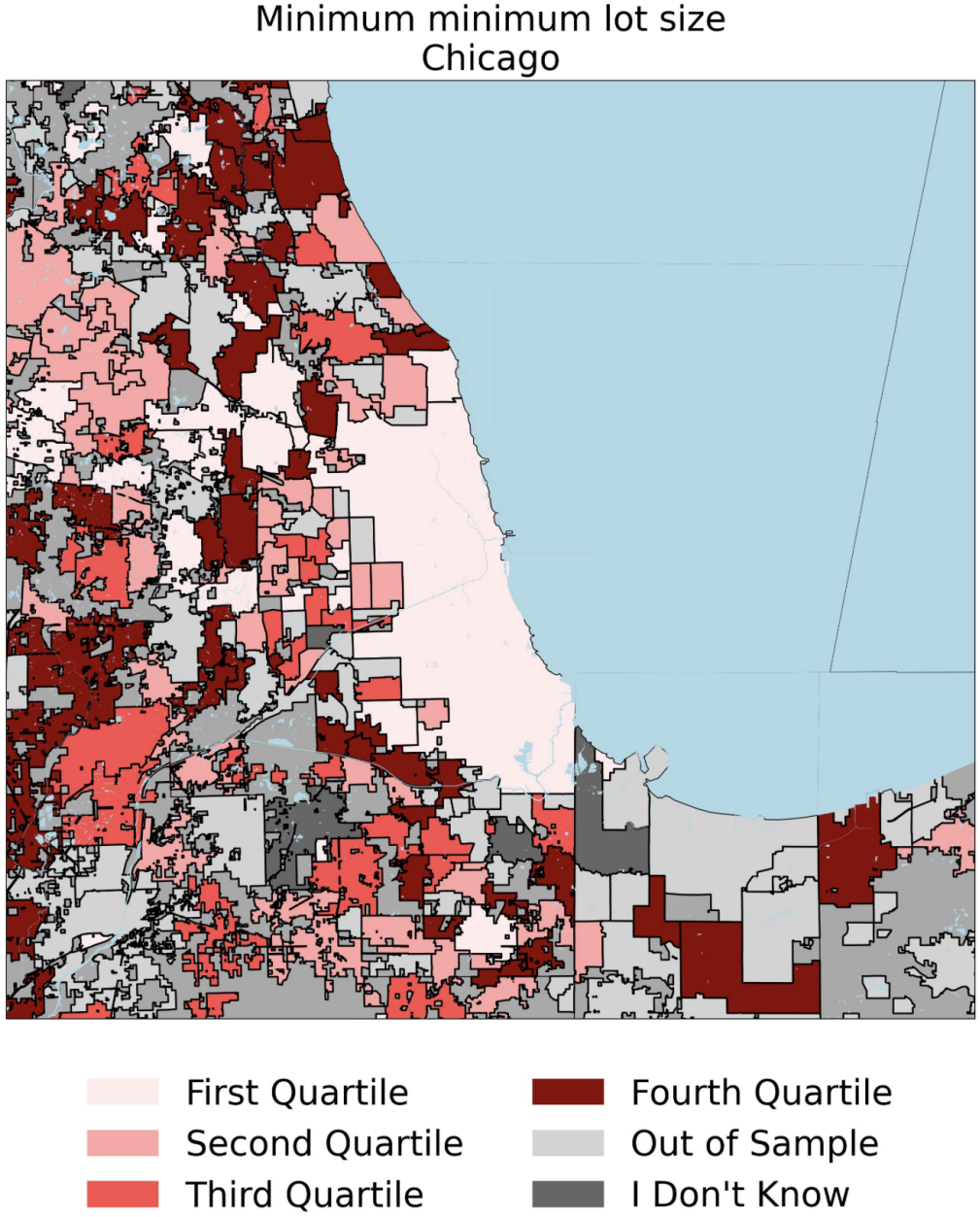


Figure 1: Automated zoning map example

Benefits of RAG

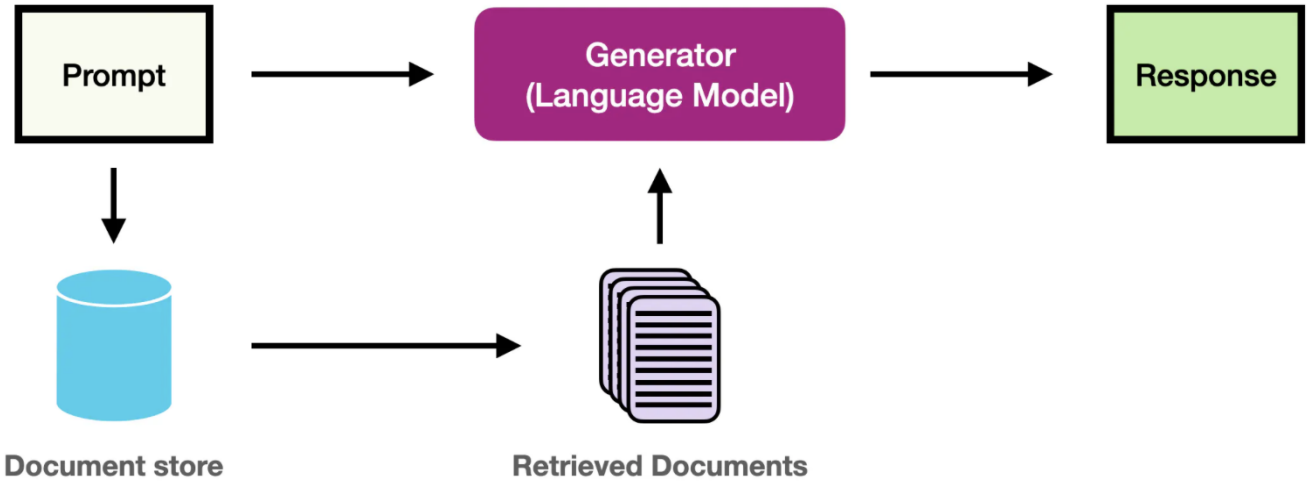
- Higher relevance and accuracy of responses
- Customize responses to use cases:
  - Past interactions (e.g tenant management)
  - Relevant related information (e.g customer demographics)
  - Proprietary style or format (e.g. response templates)
- Reduce hallucinations by referencing correct data (which can be audited)
- Incorporate up-to-date information past LLM knowledge cutoff
- Reduce data risk by adding proprietary info. only during inference, not in LLM training
- Simple way to combine SOTA LLM capabilities with expert information

RAG vs. Fine-tuning the LLM

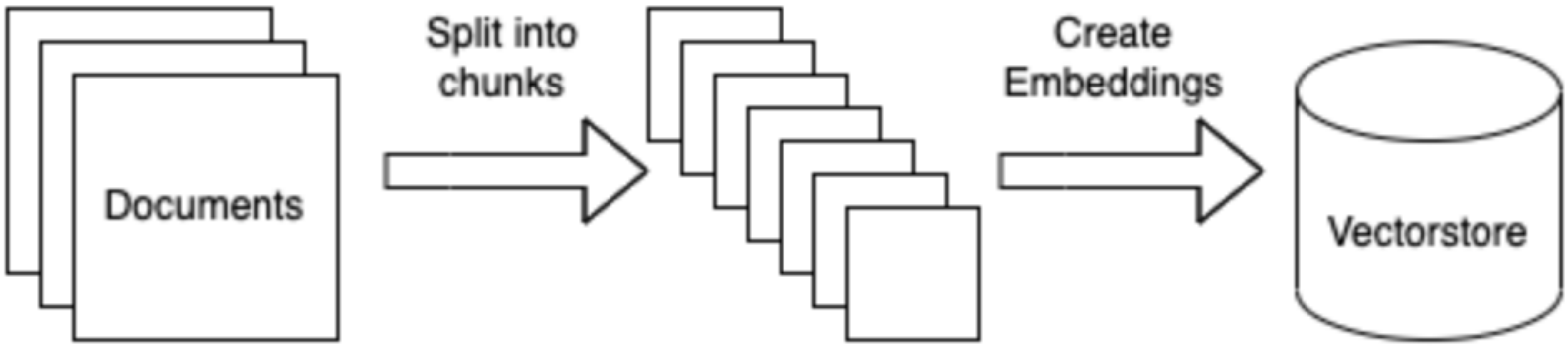
Feature Comparison	RAG	Fine-Tuning
Knowledge Updates	Direct updates ensure information remains current	Requires retraining for updates
Data Processing	Minimal processing required	Depends on high-quality data
Model Customization	May not fully customize behavior or writing style	Adjusts LLM behavior, writing style, specific domain knowledge
Interpretability	Responses traceable to specific data sources	Black box, lower interpretability
Computational Resources	Supports retrieval strategies, requires database maintenance	High-quality training data, advanced computational resources
Latency Requirements	Higher latency due to retrieval	Lower latency

RAG Process Overview

1. Input text cleaning and chunking
2. Embedding & indexing
3. Retrieval based on prompt
4. Generation with retrieval-augmented prompt

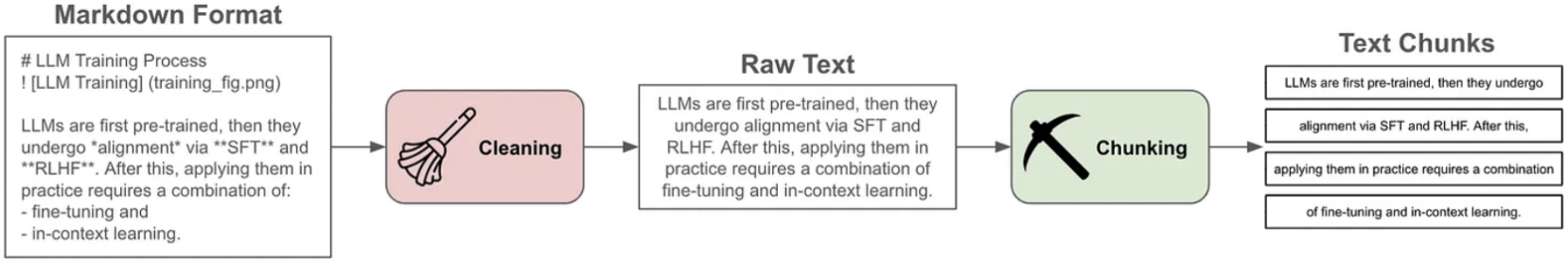


Input text ingestion



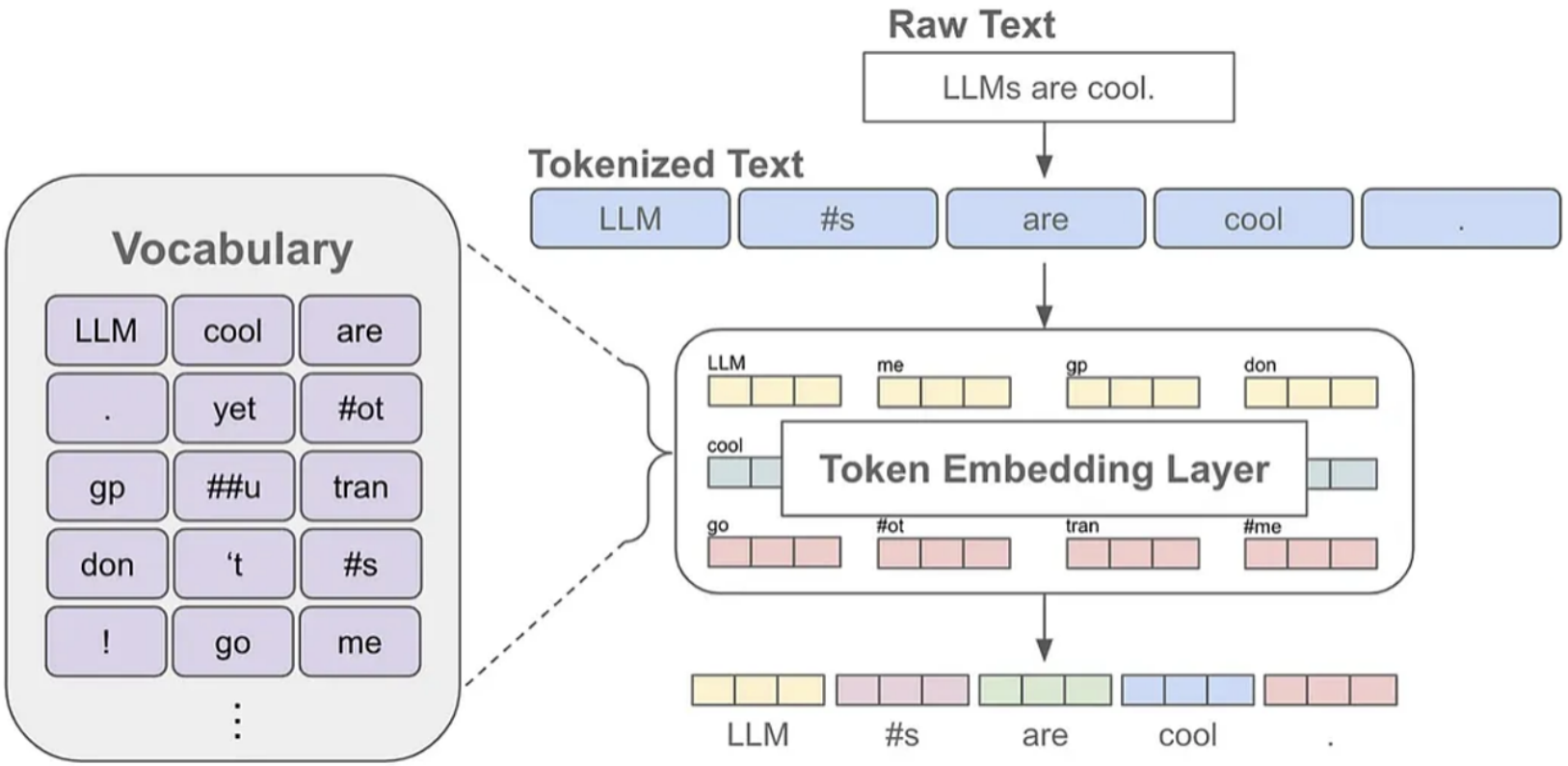
Input text preparation

- LLMs work on *tokens*, so redundant formatting adds noise
- LLMs (currently) have context window limitations - can only add limited addl. information into the prompt
- We need to process input text into smaller chunks for retrieval



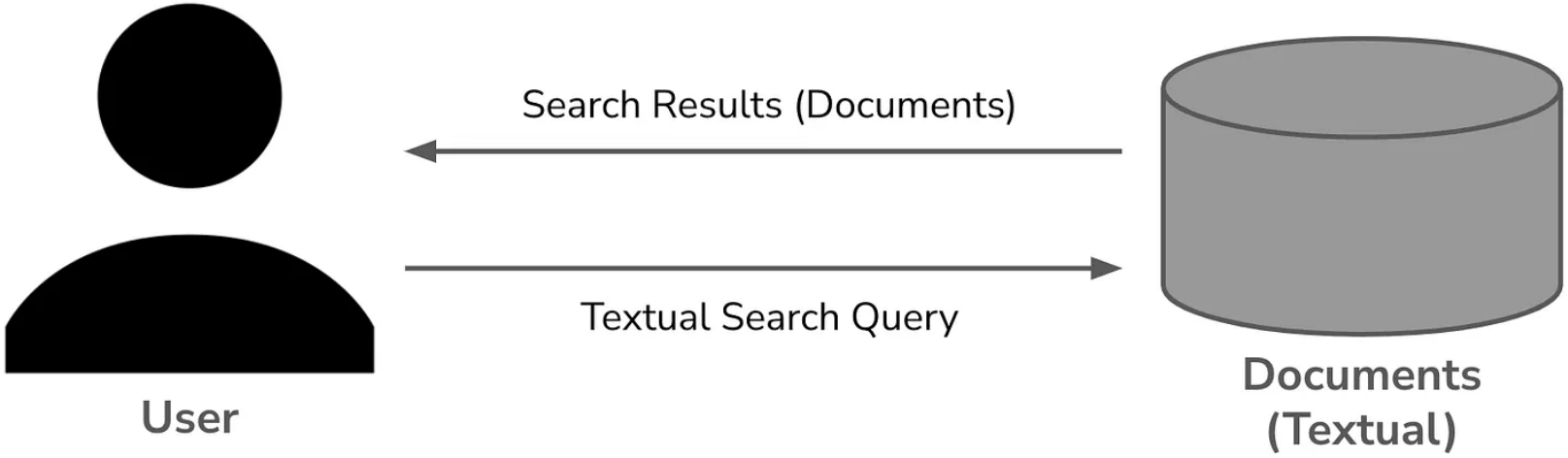
Data preprocessing (cleaning and chunking) for RAG

Embedding

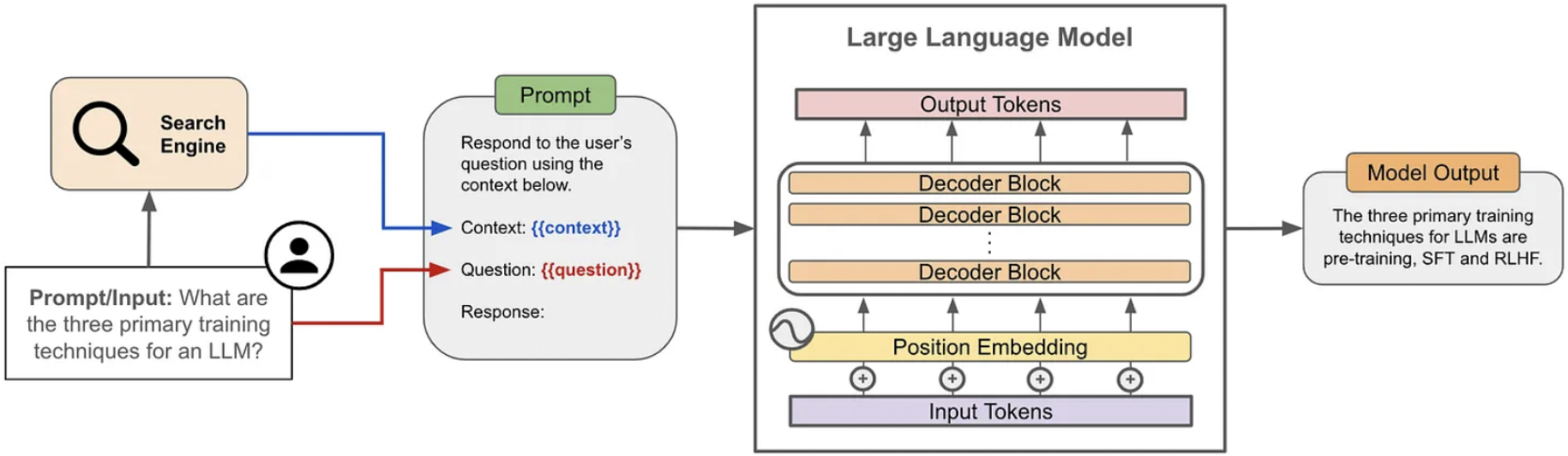

Raw Text
LLMs are cool.
Tokenized Text
LLM
#s
are
cool
.
Vocabulary
LLM
cool
are
.
yet
#ot
gp
##u
tran
don
't
#s
!
go
me
LLM
me
gp
don
cool
Token Embedding Layer
go
#ot
tran
#me
LLM
#s
are
cool
.

Retrieval

- Goal of retrieval is to find relevant textual chunks in the database that help the LLM respond to the query
- This is “just a search engine” – need to define what *relevant* means to get useful results
  - “Semantic” search using similarity in embeddings
  - “Lexical” search using keywords
  - Combination of semantic & lexical search or other search methods



RAG Prompting



RAG Example: Class Chatbot

How to Implement RAG

- Evaluate different parts of the pipeline separately: retrieval, generation etc.
- Test and iterate on prompt designs
- Think about what *relevant* means in your context: do you want retrieved text to be different, similar, diverse etc.
  - Can add a selection module (e.g. additional LLM call) that selects right input text from a broader set
- Consider context *layout* in the prompt, e.g. consider “lost in the middle” issue of LLMs, repetition etc.
- Choose applications that work with *specific* pieces of input text, e.g. *not* “how many mentions of X across the whole text”

Assignment: Create your own Chatbot (see handout)

1. *Think about a task or business problem from your own experience or that you know other people are facing. Choose a task that is suitable for automation or support using Retrieval-Augmented Generation (RAG).*
2. *Find documents that will be used as your database for RAG.*
3. *Build a chatbot using the OpenAI chatbot creation tool.*

. . . and share your chatbot with the class / explore other students' bots!

Transforming Cities: How AI might Change Real Estate Assets

1. **Geographic location**
   - Clustering of AI companies and investments around tech markets (e.g. SF) - shifts office demand and incomes
2. **Shift between asset classes**
   - AI development calls for more and better data centers,energy grids and connectivity infrastructure.
   - Might interact with office demand (more in later classes!)
3. **New asset and product types**
   - Intelligent buildings and AI-enabling and -enabled infrastructure improvements (e.g. HVAC optimization)
   - Integration with AI-enabled robotics, sensors, automation tools in all asset classes

Transforming Cities: How AI might Change Real Estate Assets

4. **Investment process**
   - AI-powered underwriting and processes enable faster and more frequent transactions
   - Expansion of “space as a service” models due to better automation *and* customization (more in later classes!)
5. **Design and space function**
   - Experience-driven building designs with customizable environments
   - Faster iteration on building and interior design process, immersive sales processes

Risks of Generative AI

- Data quality, IP rights, privacy and data security (e.g. storage of building sensor data)
- Safety standards and quality control for automated AI features (e.g. chatbot negotiating lease)
- Environmental issues, e.g. carbon emissions from computation
- Transition issues for workers

Wrap-up

Recap:

- Making AI useful requires identifying automatable tasks (e.g. BEAST method)
- Minimal Prompt Engineering can substantially improve LLM performance (context, examples, chain-of-thought)
- Use RAG to adapt LLMs to specific business use cases and local data

Next Week:

- Build and share your chatbot
- Automated valuation models & machine learning for pricing
- Nick Bruce, Arqitel

Guiding Principles for Effective Prompts

1. **Conciseness and Clarity**
   - Avoid being wordy and ambiguity
   - Be specific to guide the model effectively.
   - Use affirmative language and repeat important parts
2. **Contextual Relevance**
   - Provide relevant context.
   - Use domain-specific terms and situational descriptions.
3. **Task Alignment**
   - Align the prompt with the task.
4. **Example Demonstrations**
   - Include input-output pairs for complex tasks.
   - Useful for “few-shot” or “zero-shot” learning.
5. **Avoiding Bias**
   - Minimize biases in prompt design.
   - Use neutral language, especially for sensitive topics.
6. **Incremental Prompting**
   - Break task down into simpler steps
   - Useful for tasks requiring a logical “chain-of-thought”