

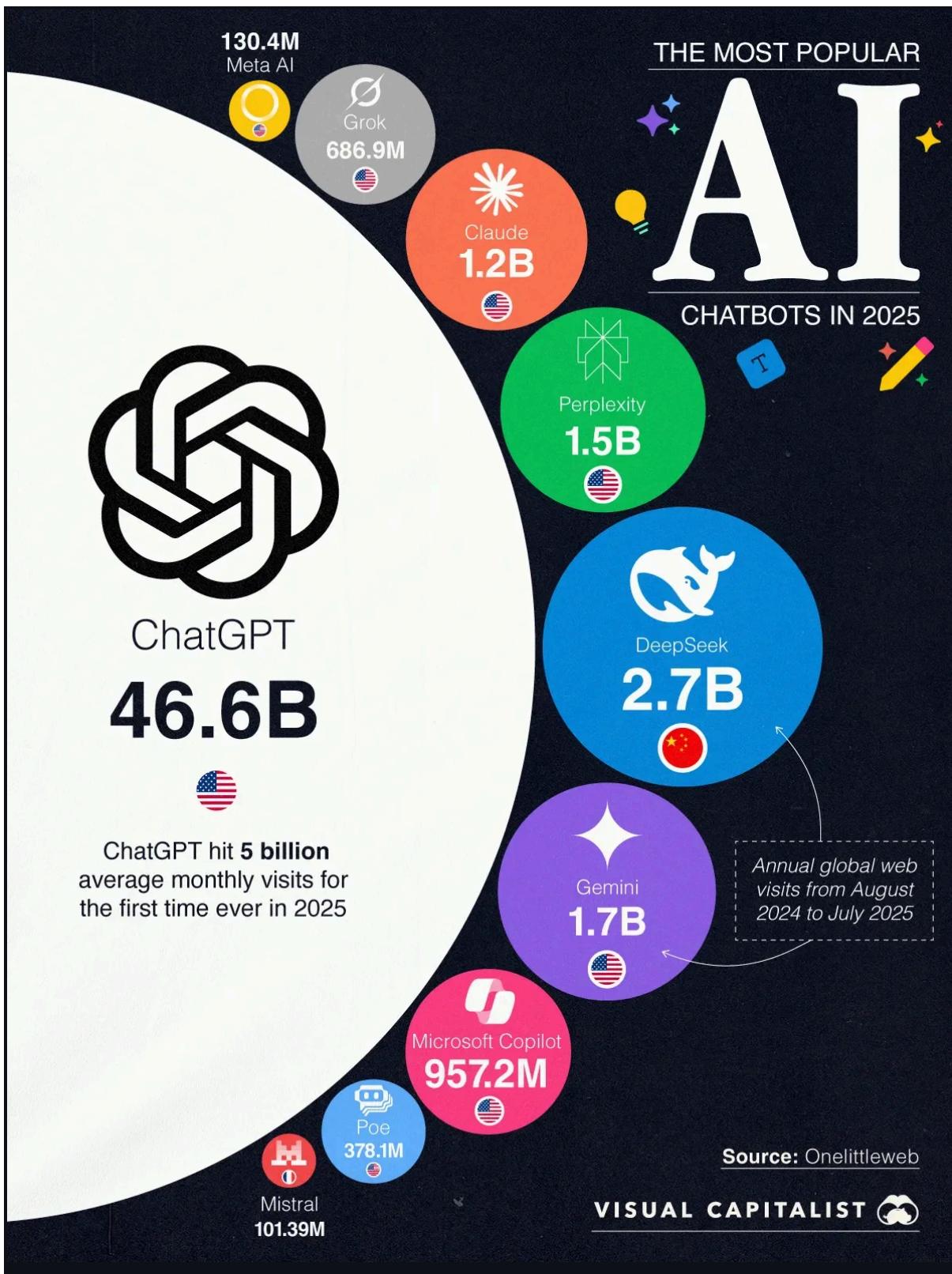
Prompt and Context Engineering

Tutorial for Beginners: A

Comprehensive Guide to Effective AI

Communication

[Panaversity YouTube Class Playlist](#)



Key Takeaways

- With 46.59B visits, ChatGPT accounts for more than 83% of total traffic among the top 10 chatbots.

- The second most-used chatbot, DeepSeek at 2.74B visits, has barely 6% of ChatGPT's traffic.
- While traffic is concentrated, the list includes a mix of U.S., Chinese, and European players.

How LLM Works

[How LLMs Work: Top 10 Executive-Level Questions](#)

Understand the Power of Prompts: Context Engineering for Agentic AI Developers, Image and Video Generation, UX/UI Design and UI Development

To understand the power of LLMs and prompt engineering go through these tutorials:

- [Complete Guide to Context Engineering for AI Agents](#)
- [Nano Banana Tutorial](#)
- [Google's Veo 3: A Guide With Practical Examples](#)
- [UX Design by Prompting](#)
- [UI Development by Prompting](#)

Which is the best LLM?

See how leading models stack up across text, image, vision, and beyond. This page gives you a snapshot of each Arena:

<https://lmarena.ai/leaderboard>

Use these Prompt Engineering Tools to Learn

<https://platform.openai.com/chat/>

<https://aistudio.google.com/>

<https://console.anthropic.com/>

Prompt Coach"

Here's a reusable "Prompt Coach" prompt you can keep handy. You'll paste this into ChatGPT (or any LLM), then just drop in your messy idea, and it will rewrite it into a polished, effective prompt for you:

Copy Paste this in your LLM:

You are my Prompt Coach. I will give you a rough or unclear prompt.

Your task is to:

1. Clarify it
2. Add missing context
3. Structure it for best results
4. Suggest 2-3 alternative versions (different styles: simple, detailed, structured)

Here's my rough prompt: [INSERT YOUR PROMPT HERE]

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What is Prompt Engineering?

Prompt engineering is the art and science of crafting instructions that guide AI language models to produce desired outputs. Think of it as learning to communicate effectively with AI systems to achieve specific goals.

Why is it important?

- You don't need to be a programmer to use AI effectively
- Good prompts can dramatically improve AI performance
- It's an iterative skill that improves with practice
- It's becoming essential for productivity in many fields

Prompt engineering vs. context engineering

Prompt engineering = crafting the *instruction* you give the model. Context engineering = curating the *information* the model can see when following that instruction.

Quick contrast

Aspect	Prompt engineering	Context engineering
Goal	Tell the model <i>how to behave and what to produce</i>	Give the model the <i>facts/examples it should rely on</i>
Levers	Wording, structure, roles, constraints, output schema, few-shot examples	Retrieval (RAG), documents, knowledge bases, tools/APIs, memory, state across turns
Typical changes	"Be concise. Return valid JSON with fields X/Y/Z."	"Attach the company glossary, latest policy PDF, and retrieved passages for this query."
Failure mode	Vague instructions → messy/incorrect format	Missing/irrelevant info → hallucinations/outdated answers
Ownership	UX/prompt designers, app devs	Data/ML/platform teams (pipelines, indexing, chunking, evals)

How they work together

- Start with a good prompt: clear task, constraints, and an output contract (e.g., JSON schema).
- Then ground it with context: supply only the *most relevant* passages, tables, and tool results.
- The prompt guides *behavior*, the context supplies *knowledge*. You usually need both.

Concrete examples

1. Invoice → JSON extractor
 - *Prompt engineering*: “Extract fields {vendor, date, total}. Return JSON only. If a field is missing, use null.”
 - *Context engineering*: Provide a few labeled examples and attach the vendor’s invoice spec retrieved via embeddings.
2. Policy Q&A bot
 - *Prompt engineering*: “Answer using the attached passages; if unsure, say ‘Not in policy.’ Cite section IDs.”
 - *Context engineering*: RAG over your policy repo (chunking, metadata filters like `department=HR`, freshness boosts), plus a recency cache for updates.
3. Agentic workflow
 - *Prompt engineering*: Tool-use instructions and function signatures.
 - *Context engineering*: Feed tool responses (DB rows, API payloads) back into the context window each step; maintain short-term memory/state.

Practical tips

- Keep prompts short, specific, and testable; define output schemas.
- Prefer few-shot examples only when they generalize; otherwise move them into retrieval.
- For context: optimize chunking, ranking, deduping, and token budgets; log what was retrieved for each answer.
- Add citations and “answer only from context” instructions when correctness matters.
- Evaluate both layers separately: prompt A/B tests and retrieval quality (precision/recall, groundedness).

One-liner: Prompt engineering is *how you ask*; context engineering is *what you show*. Combine them for reliable, scalable LLM apps.

Understanding Large Language Models

How LLMs Work (The Basics)

Large Language Models are prediction engines that:

- Take text input (your prompt)
- Predict the next most likely word/token
- Continue this process to generate complete responses
- Base predictions on patterns learned from training data

Key Concept: Autocompletion

LLMs don't "understand" in the human sense—they're sophisticated autocomplete systems. Your prompt sets up the context for what should come next.

Essential Configuration Settings

Before diving into prompt techniques, understand these key parameters that control AI behavior:

Temperature (0-1)

- Low (0-0.3): Focused, consistent, deterministic responses
- Medium (0.4-0.7): Balanced creativity and consistency
- High (0.8-1.0): Creative, diverse, but potentially unpredictable

When to use:

- Temperature 0: Math problems, factual questions
- Temperature 0.7: Creative writing, brainstorming
- Temperature 0.9: Poetry, experimental content

Output Length/Token Limits

- Controls maximum response length
- Higher limits = more computational cost
- Set appropriately for your task needs

Top-K and Top-P (Nucleus Sampling)

- Top-K: Limits choices to top K most likely tokens
- Top-P: Limits choices based on cumulative probability
- Work together with temperature to control randomness

Recommended starting points:

- Conservative: Temperature 0.1, Top-P 0.9, Top-K 20
- Balanced: Temperature 0.2, Top-P 0.95, Top-K 30
- Creative: Temperature 0.9, Top-P 0.99, Top-K 40

Fundamental Prompting Techniques

1. Zero-Shot Prompting

The simplest approach—just ask directly without examples.

Example:

```
Classify this movie review as positive, negative, or neutral:  
"The film was visually stunning but the plot felt rushed."
```

When to use:

- Simple, well-defined tasks
- When the model has clear knowledge of the domain
- Quick one-off requests

2. One-Shot Prompting

Provide a single example to guide the response format.

Example:

```
Translate English to French:
```

```
English: "Hello, how are you?"  
French: "Bonjour, comment allez-vous?"
```

```
English: "Where is the library?"
```

```
French:
```

3. Few-Shot Prompting

Provide multiple examples to establish a clear pattern.

Example:

```
Convert customer feedback to structured data:
```

```
Feedback: "Great service, but food was cold"  
JSON: {"service": "positive", "food": "negative", "overall": "mixed"}  
  
Feedback: "Amazing experience, will definitely return"  
JSON: {"service": "positive", "food": "positive", "overall": "positive"}  
  
Feedback: "Terrible food and rude staff"  
JSON:
```

Best practices:

- Use 3-5 examples for most tasks
- Include diverse examples
- Mix up the classes in classification tasks
- Ensure examples are high-quality and consistent

4. System Prompting

Set overall context and behavior guidelines.

Example:

You are a helpful travel guide. Provide practical, accurate information about destinations. Always include:

- Key attractions
- Local customs to be aware of
- Budget considerations
- Best time to visit

User: Tell me about visiting Tokyo.

5. Role Prompting

Assign a specific character or expertise to the AI.

Example:

Act as an experienced software architect. I need help designing a scalable web application for 1 million users. What architecture patterns should I consider?

Effective roles:

- Subject matter expert (doctor, lawyer, teacher)
- Creative roles (writer, designer, poet)
- Analytical roles (data analyst, consultant)
- Communication styles (friendly tutor, formal advisor)

6. Contextual Prompting

Provide specific background information relevant to the task.

Example:

Context: You're writing for a tech blog aimed at beginners who have never coded before.

Write a 200-word explanation of what an API is, using simple language and practical examples.

Advanced Prompting Strategies

Chain of Thought (CoT) Prompting

Encourage step-by-step reasoning for complex problems.

Example:

Solve this step by step:

If I was 6 when my sister was half my age, how old is my sister when I'm 40?

Let me think through this step by step:

When to use:

- Math problems
- Logical reasoning
- Complex analysis
- Multi-step processes

Best practices:

- Use "Let's think step by step" or similar phrases
- Set temperature to 0 for consistent reasoning
- Extract final answers separately from reasoning

Self-Consistency

Generate multiple reasoning paths and select the most common answer.

Process:

1. Ask the same question multiple times with different phrasings
2. Compare the answers
3. Choose the most frequently occurring result

Example:

Question: If a store offers a 20% discount on a \$50 item, what is the final price?

Generate 3 different reasoning paths for this question and select the most consistent answer.

Path 1: To find the final price, calculate the discount: 20% of \$50 is $0.20 \times 50 = \$10$. Subtract this from the original price: $\$50 - \$10 = \$40$. The final price is \$40.

Path 2: A 20% discount means paying 80% of the original price. So, 80% of \$50 is $0.80 \times 50 = \$40$. Therefore, the final price is \$40.

Path 3: Compute the discount amount: $20\% = 0.20$, so $0.20 \times \$50 = \10 off. The original price is \$50, so after the discount, it's $\$50 - \$10 = \$40$. The final price is \$40.

Most common answer: \$40

Explanation of Concept: Self-Consistency involves generating multiple answers to the same question using varied reasoning approaches to ensure reliability. By comparing the results, you select the most frequent or consistent outcome, reducing the chance of errors from a single flawed reasoning path. This method leverages the model's ability to approach the problem from different angles, increasing confidence in the final answer when all paths converge, as seen here with the consistent result of \$40.

Step-Back Prompting

Ask a more general question first, then use that context for the specific question.

Example 1:

First, what are the key principles of good user interface design?

[Get response]

Now, using those principles, redesign this mobile app's login screen:
[description]

Example 2: Question: How should I optimize the loading speed of my e-commerce website?

Step 1: First, what are the key factors that generally affect website loading speed?

Response: Key factors include:

- Server response time (hosting quality, server location)
- Image and asset optimization (file size, compression)
- Code efficiency (minifying CSS/JavaScript, reducing HTTP requests)
- Caching strategies (browser caching, CDNs)
- Third-party scripts (ads, analytics)

Step 2: Using these factors, provide specific recommendations to optimize the loading speed of an e-commerce website with heavy product images and multiple third-party plugins.

Response:

1. **Server Optimization**: Choose a reliable hosting provider with servers close to your audience. Enable server-side caching (e.g., Redis or Varnish).
2. **Image Optimization**: Compress product images using formats like WebP. Implement lazy loading to defer off-screen images.
3. **Code Efficiency**: Minify CSS and JavaScript files. Combine small files to reduce HTTP requests.
4. **Caching**: Use a Content Delivery Network (CDN) like Cloudflare to cache static content globally. Set browser cache headers for repeat visitors.
5. **Third-Party Plugins**: Audit and remove unnecessary plugins. Asynchronously load scripts for analytics or ads to avoid blocking page rendering.

Explanation of Concept: Step-Back Prompting involves first asking a broader, foundational question to establish key principles or context before tackling the specific task. This approach ensures the model grounds its response in general knowledge (e.g., factors affecting website speed) before applying it to the specific problem (e-commerce site optimization). By breaking the task into two steps, the model produces more informed and structured recommendations, reducing the risk of overlooking critical factors.

ReAct (Reasoning + Acting)

Combine reasoning with tool use or actions.

Example 1:

I need to find out how many children the members of Metallica have in total.

Thought: I need to find information about each band member and their children.

Action: Search for "Metallica band members"

Observation: [results]

Thought: Now I need to search for each member individually...

Example 2:

Question: What is the current population of Tokyo, and how does it compare to New York City?

Thought: I need to find the current population of Tokyo and New York City to compare them. I should start by searching for the latest population data for Tokyo.

Action: web_search

```
<parameter name="query">current population of Tokyo 2025</parameter>
```

Observation: [Assume tool response: According to recent estimates, Tokyo's population in 2025 is approximately 37.4 million in the metropolitan area.]

Thought: Now I have Tokyo's population. Next, I need the population for New York City.

Action: web_search

```
<parameter name="query">current population of New York City 2025</parameter>
```

Observation: [Assume tool response: New York City's metropolitan area population in 2025 is estimated at about 23.6 million.]

Thought: With both figures, I can compare them. Tokyo has a larger population than New York City by about 13.8 million people.

Final Answer: Tokyo's population is approximately 37.4 million, compared to New York City's 23.6 million, making Tokyo significantly larger.

Explanation of Concept: ReAct (Reasoning + Acting) is a prompting strategy that interleaves reasoning steps (Thoughts) with actions (tool calls or external queries) to solve complex problems iteratively. Each cycle includes a Thought (planning the next step), an Action (executing a tool or search), and an Observation (processing the result). This loop continues until the question is resolved, allowing the model to dynamically gather information and refine its approach. It's particularly useful for tasks requiring real-time data or multi-step verification, as demonstrated by sequentially fetching and comparing population data.

Tree of Thoughts (ToT)

Explore multiple reasoning branches simultaneously for complex problems.

When to use:

- Creative problem solving
- Strategic planning
- Complex decision-making
- Tasks requiring exploration of alternatives

Example:

Question: What is the best marketing strategy for launching a new eco-friendly clothing brand targeting young adults?

Task: Explore multiple strategic approaches, evaluate them, and select the best one.

Branch 1: Social Media Campaign Thought: Young adults are active on platforms like Instagram and TikTok. A campaign using influencers could build brand awareness.

Exploration:

- Pros: High engagement, visually appealing for clothing, cost-effective with micro-influencers.
 - Cons: Risk of inauthentic partnerships, oversaturation in influencer marketing.
- Evaluation: Strong for visibility but needs unique content to stand out. Score: 8/10.

Branch 2: Sustainable Pop-Up Events Thought: Hosting pop-up shops at eco-conscious festivals or college campuses could create direct engagement.

Exploration:

- Pros: Hands-on experience with products, builds community, aligns with eco-friendly values.
 - Cons: High logistical costs, limited geographic reach.
- Evaluation: Great for brand authenticity but resource-intensive. Score: 7/10.

Branch 3: Collaborative Partnerships Thought: Partnering with eco-friendly brands (e.g., sustainable accessories) could cross-promote to aligned audiences.

Exploration:

- Pros: Expands reach via partner networks, reinforces eco-mission.
 - Cons: Complex coordination, potential brand dilution.
- Evaluation: Effective for niche targeting but requires careful partner selection. Score: 7.5/10.

Synthesis: Combine a social media campaign (Branch 1) with selective pop-up events (Branch 2) for maximum impact. Use partnerships (Branch 3) to amplify reach at events.

Final Strategy: Launch with a TikTok influencer campaign showcasing eco-friendly clothing, paired with pop-up shops at green festivals to engage young adults directly. Collaborate with a sustainable accessory brand to co-promote at events.

Explanation of Concept: Tree of Thoughts (ToT) involves generating multiple reasoning branches to explore different solutions to a problem, evaluating each, and synthesizing the best ideas into a final answer. Each branch represents a distinct approach, which is explored, assessed for pros and cons, and scored. This method

is ideal for complex, open-ended tasks like strategic planning, as it encourages creative exploration and systematic comparison, as shown in the marketing strategy example above.

Best Practices for Effective Prompts

1. Be Specific and Clear

Bad:

Write a 500-word informative article about the health benefits of owning a dog.

Good:

Write a 500-word informative article about the health benefits of owning a dog, focusing on mental health, physical activity, and social connections. Use a friendly, accessible tone for general readers.

2. Use Action Verbs

Be explicit about what you want the AI to do:

- Analyze, Compare, Create, Describe, Evaluate
- Extract, Generate, List, Rank, Summarize
- Translate, Write, Explain, Classify

3. Provide Examples When Possible

Examples are the most powerful way to communicate your expectations.

4. Structure Your Prompts

Use clear formatting:

Task: [What you want done]

Context: [Background information]

Format: [How you want the output structured]

Example: [Sample of desired output]

5. Use Instructions Over Constraints

Better:

Write a professional email summarizing the key points from our meeting.

Avoid:

Write an email, but don't make it too long or too informal or too detailed.

6. Control Output Format

Specify exactly how you want the response structured:

Return your answer as a JSON object with the following structure:

```
{  
  "main_idea": "string",  
  "supporting_points": ["string", "string"],  
  "confidence_level": "high/medium/low"  
}
```

7. Use Variables for Reusability

Role: You are a {expertise} expert

Task: Analyze the {document_type} and provide recommendations for {target_audience}

Context: This is for a {industry} company with {company_size} employees

8. Iterate and Document

- Keep track of what works and what doesn't
- Document your successful prompts
- Test variations to improve performance

Common Pitfalls and How to Avoid Them

1. Ambiguous Instructions

Problem: Vague requests lead to unpredictable outputs
Solution: Be specific about what you want

2. Contradictory Instructions

Problem: Conflicting requirements confuse the model
Solution: Review prompts for internal consistency

3. Too Many Constraints

Problem: Over-constraining limits model creativity
Solution: Focus on positive instructions rather than long lists of don'ts

4. Ignoring Token Limits

Problem: Responses get cut off mid-sentence
Solution: Set appropriate limits and structure accordingly

5. Not Testing Variations

Problem: Assuming first attempt is optimal
Solution: Test different phrasings, examples, and approaches

Hands-On Examples

Example 1: Content Creation

Task: Create a social media post

Basic prompt:

Write a social media post about coffee.

Improved prompt:

Write an engaging Instagram post for a local coffee shop's new seasonal drink.

Context: Fall season launch of Pumpkin Spice Maple Latte

Audience: Coffee enthusiasts aged 25-40

Tone: Warm, inviting, not overly promotional

Format:

- Main text (150 characters max)

- 3-5 relevant hashtags

- Call to action

Include sensory details about taste and aroma.

Example 2: Data Analysis

Task: Analyze customer feedback

Basic prompt:

Write a code snippet to analyze mood from reviews.

Improved prompt:

Analyze the following customer reviews and provide insights.

Reviews: [paste reviews here]

Please provide:

1. Overall sentiment breakdown (positive/negative/neutral percentages)
2. Top 3 most mentioned positive aspects
3. Top 3 most mentioned concerns or issues
4. Specific recommendations for improvement
5. Confidence level in your analysis

Format as a structured report with clear headings.

Example 3: Code Generation

Task: Create a function

Basic prompt:

Write a function to sort a list.

Improved prompt:

Write a Python function that:

Requirements:

- Sorts a list of dictionaries by a specified key
- Handles missing keys gracefully (items without key go to end)
- Supports both ascending and descending order
- Includes proper error handling
- Has clear documentation

```
Example usage:  
data = [{"name": "Alice", "age": 30}, {"name": "Bob", "age": 25}]  
result = sort_by_key(data, "age", descending=False)
```

Please include:

- Function definition with type hints
- Docstring with parameters and return value
- Example usage
- Brief explanation of the approach

Testing and Iteration

1. Create a Testing Framework

A testing framework is a documented, organized system for recording and analyzing how different prompts perform when interacting with an AI model. It involves creating a standardized way to:

- Record prompt variations, their goals, and settings (e.g., model used, temperature).
- Test these prompts to assess the quality of the AI's outputs.
- Evaluate results based on specific criteria (e.g., accuracy, relevance, style).
- Iterate by refining prompts based on insights from the tests.

The framework ensures that prompt engineering is not a haphazard process but a methodical one, allowing users to identify what works, what doesn't, and how to improve prompts over time.

Document your prompts systematically:

Prompt Version	Goal	Model	Temperature	Output Quality	Notes
v1.0	Generate blog post	GPT-4	0.7	Good	Too formal
v1.1	Generate blog post	GPT-4	0.7	Better	Added tone guidance

2. A/B Test Different Approaches

A/B testing in prompt engineering involves creating and trying out multiple versions of a prompt (e.g., different wordings, structures, examples, or settings like temperature) to see which version yields the most accurate, relevant, or high-quality output from the AI. It's a systematic way to experiment and optimize prompts by comparing their performance side by side.

Try variations:

- Different example sets
- Various instruction phrasings
- Different temperature settings
- Alternative output formats

3. Evaluate Results

Consider:

- Accuracy: Does it answer correctly?
- Relevance: Is it on-topic?
- Completeness: Does it cover everything needed?
- Style: Does it match the desired tone?
- Format: Is it structured as requested?

4. Common Evaluation Metrics

- Consistency: Same prompt, similar outputs
- Following instructions: Adherence to specific requirements
- Creativity (when desired): Novel and interesting responses
- Factual accuracy: Correctness of information

Advanced Tips for 2025

1. Leverage Structured Outputs

Use JSON, XML, or other structured formats for complex data:

```
return analysis as JSON.  
{  
  "summary": "brief overview",  
  "key_insights": ["insight1", "insight2"],  
  "recommendations": [  
    {  
      "action": "specific action",  
      "details": "detailed steps"  
    }  
  ]  
}
```

```
        "priority": "high/medium/low",
        "timeline": "timeframe"
    }
]
```

2. Context Management

For long conversations:

- Summarize previous context
- Use system messages effectively
- Break complex tasks into smaller parts

3. Multi-Modal Prompting

When working with models that support images:

- Be explicit about what to look for in images
- Combine text and visual instructions
- Use images as examples or context

4. Prompt Chaining

Break complex tasks into steps:

Step 1: Research the topic

Step 2: Create an outline based on research

Step 3: Write the full content based on outline

Resources and Next Steps

Tools and Platforms

- OpenAI Playground: Test prompts with GPT models
- Anthropic Console: Experiment with Claude
- Google AI Studio: Try Gemini models
- Prompt optimization tools: Available from various providers

Learning Resources

- Model documentation and guides
- Community forums and Discord servers
- GitHub repositories with prompt examples
- Academic papers on prompt engineering techniques

Practice Projects

1. Personal Assistant: Create prompts for scheduling, email drafting
2. Content Creation: Develop templates for different types of writing
3. Data Analysis: Build prompts for interpreting datasets
4. Code Review: Create prompts for code analysis and improvement

Building a Prompt Library

- Create templates for common tasks
- Document what works for different models
- Share and learn from other practitioners
- Keep updating as models improve

Mixture-of-Experts (MoE) and Prompt Engineering

Mixture-of-Experts (MoE) is a machine learning architecture designed to improve the efficiency and scalability of large models, particularly in the context of Large Language Models (LLMs). It draws from the concept of dividing complex tasks among specialized "experts" in a system, allowing the model to activate only a subset of its parameters for a given input rather than using the entire model every time. This sparse activation leads to computational savings while maintaining or even enhancing performance.



MoE Implementation Status in Frontier Models

Below is an table summarizing the Mixture-of-Experts (MoE) implementation status based on available information up to August 2025.

LLM	Developer	MoE Implementation	Details

GPT-5	OpenAI	Yes (Speculated)	Likely uses MoE with dynamic routing for reasoning levels. Estimated ~2T total parameters. No official confirmation, but performance (e.g., 74.9% SWE-bench) suggests sparse MoE-like design.
Grok 4	xAI	Yes (Confirmed)	Utilizes MoE with multi-agent architecture. ~500B total parameters, sparse activation. Strong performance on ARC-AGI (16.2% with Thinking Mode). Expert count not disclosed.
Gemini 2.5 Pro	Google	Yes (Confirmed)	Confirmed MoE with advanced reasoning capabilities. Details on sparsity and expert count not specified, but designed for efficient scaling.
Claude 4	Anthropic	Unknown	No confirmed details on Claude 4. Based on Claude 3.5 Sonnet, no MoE implementation is confirmed. Estimated ~400B parameters, likely dense architecture.
DeepSeek-V3	DeepSeek	Yes (Confirmed)	MoE model with 671B total parameters, 37B active per token, using DeepSeekMoE architecture with Multi-Head Latent Attention (MLA). Highly efficient, trained on 14.8T tokens for ~\$5.6M.

Notes:

- GPT-5: MoE is speculated due to its dynamic routing and massive scale (~2T parameters), suggesting a sparse architecture. No official OpenAI confirmation.
- Grok 4: Confirmed MoE with multi-agent design for specialized task handling, enhancing efficiency through sparse activation.
- Gemini 2.5 Pro: Confirmed MoE, optimized for scalability, though specific expert counts are undisclosed.
- Claude 4: No explicit data on Claude 4. Assuming similarity to Claude 3.5 Sonnet, it likely uses a dense transformer without MoE, pending new evidence.
- DeepSeek-V3: Explicitly uses MoE with 671B total parameters, activating only 37B per token via DeepSeekMoE and MLA, achieving cost-effective training and inference. Outperforms many open-source models on benchmarks like MMLU and SWE-bench.

Key Components of MoE:

1. Experts: These are specialized sub-networks (often feed-forward neural networks) within the model, each trained to handle specific types of data or tasks. For example, one expert might specialize in mathematical reasoning, another in creative writing, and so on. In advanced LLMs, there can be dozens or hundreds of experts (e.g., Mixtral 8x7B has 8 experts per layer).
2. Gating Network (or Router): This is a lightweight mechanism (typically a simple neural network) that evaluates the input and decides which experts to route the data to. It assigns weights or probabilities to experts, selecting the top-k (e.g., top 2 out of 8) most relevant ones. The output is a weighted combination of the selected experts' responses. The gating is learned during training and can be dynamic, adapting to the input.
3. Sparse Activation: Unlike dense models (e.g., GPT-3 or Llama) where all parameters are activated for every token, MoE activates only a fraction (e.g., 10-20%) of the parameters per input. This makes MoE models "conditionally compute" – they scale to trillions of parameters but run as efficiently as smaller dense models during inference.

How MoE Works in LLMs:

- Training: During pre-training, the model learns to route inputs to appropriate experts via auxiliary losses (e.g., load balancing to prevent any single expert from being overused). This is often done on massive datasets to ensure experts specialize without overlapping too much.

- Inference: For a prompt, the gating network processes the input tokens layer by layer, routing them to experts. This parallelism allows for faster training and inference on hardware like GPUs/TPUs, as unused experts can be skipped.
- Benefits:
 - Efficiency: Models like Grok-1 (314B parameters but activates ~25% per token) or Mixtral achieve high performance with lower compute costs compared to dense models of similar effective size.
 - Scalability: Enables "expert scaling" where adding more experts increases capacity without proportional compute growth.
 - Specialization: Experts can capture diverse knowledge, potentially leading to better handling of niche tasks.
- Drawbacks:
 - Routing Instability: The gating can sometimes fail to balance load, leading to inefficiencies or biases.
 - Memory Overhead: Storing many experts requires more memory, though sparsity mitigates runtime costs.
 - Interpretability Challenges: It's harder to understand why a specific expert was chosen.

MoE has become prevalent in advanced LLMs since around 2023, with models like Mistral's Mixtral, Google's Switch Transformers, and xAI's Grok-1 adopting it. By 2025, most frontier models (e.g., those from OpenAI, Google, Anthropic, and xAI) incorporate MoE variants for better parameter efficiency in the race toward AGI-scale systems.

How Does MoE Change Prompt Engineering?

Prompt engineering – the art of crafting inputs to elicit optimal responses from LLMs – traditionally focuses on clarity, structure, role-playing, chain-of-thought (CoT), and few-shot examples to guide dense models. MoE introduces nuances because of its modular, expert-based design, shifting the focus toward "expert elicitation" and robustness to routing dynamics. While core principles remain, MoE can make prompts more effective (or unpredictable) depending on how they activate the underlying experts. Here's how it impacts the practice:

1. Need for Expert-Aware Prompting:

- In MoE models, the gating mechanism interprets the input to select experts. Vague or overly broad prompts might route to generic experts, leading to mediocre outputs, while targeted prompts can "awaken" specialized ones.
- Change: Engineers must design prompts to signal specific domains. For instance, starting with "As a math expert..." might route to numerical

specialists, improving accuracy on equations. This is akin to "role-playing" but more potent due to built-in specialization.

- Example: In a dense model, a simple "Solve $2x + 3 = 7$ " works fine. In MoE, prefixing with "Using algebraic expertise:" could ensure routing to a math-focused expert, reducing errors from misrouting.

2. Enhanced Chain-of-Thought (CoT) and Multi-Step Reasoning:

- MoE's experts can handle sub-tasks modularly, so prompts that break down problems (e.g., "Step 1: Analyze facts with historical expert. Step 2: Predict with forecasting expert.") leverage routing for better decomposition.
- Change: Prompts become more "orchestrated," explicitly invoking expert-like steps. This can amplify CoT effectiveness, as different experts process intermediate steps. Studies show MoE models excel in long-context reasoning when prompts guide routing progressively.
- Tip: Use iterative prompting (e.g., via API calls) to refine outputs, as initial routing might not be perfect – re-prompt with feedback to re-route.

3. Handling Sparsity and Variability:

- Outputs can vary more across runs due to stochastic routing (if top-k selection has randomness), making deterministic prompting harder.
- Change: Emphasize consistency techniques like temperature=0 (for greedy decoding) or repeated sampling to average expert activations. Also, test prompts across multiple runs to identify routing-sensitive ones. In production, this might require "prompt ensembles" where multiple variants are tried to hit the right experts.

4. Efficiency in Prompt Length and Complexity:

- Shorter, focused prompts can efficiently activate few experts, reducing latency – a boon for real-time apps.
- Change: MoE encourages concise, intent-clear prompts over verbose ones. However, for creative or open-ended tasks, adding domain hints (e.g., "In the style of a sci-fi expert") can unlock diverse expert combinations without bloating the input.
- Few-Shot Learning: Examples in prompts help "train" the router on-the-fly, making MoE more adaptable to custom tasks than dense models, but they must align with expert domains to avoid dilution.

5. Broader Implications and Best Practices:

- Positive Shifts: MoE reduces the need for heavy fine-tuning; prompt engineering can "fine-tune" via routing. It's great for multilingual or multimodal LLMs, where prompts specify modalities to route correctly.
- Challenges: Black-box routing means trial-and-error is key – use A/B testing or logging to analyze which prompts activate desired behaviors. Ethically, be aware of potential biases if experts specialize unevenly (e.g., cultural experts).
- Evolving Landscape (as of 2025): With models like advanced Grok versions or Llama 3 MoE variants, tools like prompt optimizers (e.g., DSPy or Guidance) are adapting to simulate routing. Research suggests MoE amplifies prompt sensitivity, so hybrid approaches (combining with RAG for external knowledge) are rising.

Small wording changes can steer which experts wake up

Because a router chooses experts *based on your tokens*, small wording changes can steer which experts wake up. That means prompt craft can influence which specialization you tap.

Do more of this

1. Front-load domain signals. Put the clearest task + domain cues in the first few lines to help the router lock onto the right experts early.
 - o "Role: Financial analyst. Task: T0-K variance analysis. Output: tabular summary + bullet risks."
2. Use unambiguous, domain-specific vocabulary. The router keys off tokens; plain, on-topic terms beat clever phrasing or euphemisms.
3. Separate mixed tasks. If you combine coding, legal, and marketing in one shot, the router may oscillate experts. Break it into steps or run sequential prompts.
4. Match examples to the task. Few-shot exemplars should be in the *same domain, format, and language* as your goal—this strongly reinforces the intended experts.
5. Be explicit about language and style. Start with: "Language: Urdu. Style: concise, technical." Multilingual MoE models often have language-specialized experts.
6. Stabilize when you need consistency. Lower temperature/top-p reduces token drift, which indirectly reduces expert churn across the generation.
7. Keep retrieval context clean. In RAG, put a short task summary *before* the docs, and keep the docs on-topic; noisy context can misroute tokens.

Do less of this

- Cute indirection (“you know what I mean”)—it weakens routing signals.
- Overlong preambles that bury the true task. MoE routes per token, but early tokens set the scene.
- Mashing multiple formats (e.g., code + poetry + SQL) in one go—split it.

A routing-friendly prompt skeleton

System/intro:

Role: <domain persona>
Task: <crisp objective>
Audience: <who/level>
Language: <one language only>
Output: <format + constraints>

Instructions:

- 1) <step>
- 2) <step>
- 3) <step>

Examples (optional, tightly matched):

<short in-domain example(s)>

Context (if any, trimmed to essentials):

<RAG snippets or data>

Now solve the task.

Troubleshooting with MoE models

- Inconsistent answers across runs? Add sharper domain anchors at the top; reduce temperature; include one very short, in-domain example.
- It “misses” the skill you want (e.g., math vs. writing)? Use explicit skill tags (“Task type: quantitative proof/derivation”) and show the target format in a tiny exemplar.
- Mixed-topic responses? Split the request; or ask for a plan first, then execute each step in a follow-up.

Bottom line: MoE doesn’t change the *foundation* of prompt engineering, but it raises the leverage of clear, early, domain-specific signals because they literally decide which specialists inside the model wake up for your tokens.

Conclusion

Prompt engineering is both an art and a science. It requires understanding how AI models work, clear communication skills, and systematic experimentation. The key to success is:

1. Start simple and add complexity gradually
2. Be specific about what you want
3. Provide examples whenever possible
4. Test and iterate to improve results
5. Document your successes for future reference

As AI models continue to evolve, prompt engineering techniques will also advance. Stay curious, keep experimenting, and remember that the best prompt is one that consistently gives you the results you need.

The future of AI interaction lies in clear, effective communication—and prompt engineering is your toolkit for making that communication as powerful as possible.