Demand for LLMs: Descriptive Evidence on Substitution, Market Expansion, and Multihoming (Preliminary, comments very much welcome.)

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Abstract

This paper documents three stylized facts about the demand for Large Language Models (LLMs) using data from OpenRouter, a prominent LLM marketplace. First, new models experience rapid initial adoption that stabilizes within weeks. Second, model releases differ substantially in whether they primarily attract new users or substitute demand from competing models. Third, multi-homing—using multiple models simultaneously—is common among apps. These findings suggest significant horizontal and vertical differentiation in the LLM market, implying opportunities for providers to maintain demand and pricing power despite rapid technological advances.

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1 Introduction

Massive investments have been undertaken by companies such as Anthropic, Google, and OpenAI to advance the state of the art in artificial intelligence. While few doubt that these investments will yield better AI models, whether these models will generate extraordinary profits remains uncertain. In one state of the world, AI models are undifferentiated and competition will result in a race to the bottom, with prices equal to marginal costs. In another state of the world, AI models are heterogeneous and customers have differentiated preferences for one model provider versus another. Which of these worlds we live in is an empirical question.

In this paper, I present descriptive evidence about demand for Large Language Models (LLMs). I use the release of three models (Claude Sonnet 3.7, Gemini Flash 2.0, and Gemini Pro 2.5) to document three stylized facts about the demand for AI models. My analysis suggests that, at least at present, LLMs are both horizontally and vertically differentiated from each other.

The stylized facts are listed below.

1. Improved models are adopted quickly, with increased demand stabilizing within a few weeks.

2. New model releases differ in the degree to which they cause substitution from existing models or expand the market.

3. There is substantial multi-homing, with users of the same app employing a mix of models.

To conduct this analysis, I use data scraped from OpenRouter, which is a marketplace for LLMs used by over a million users either directly or through popular apps such as Cline and Roo Code. OpenRouter provides an API that helps app developers and other users manage their interactions with a variety of LLMs, including providing tools for routing API calls across models and providers depending on price and latency. My dataset consists of daily usage by model between January 11, 2025 and April 11, 2025. In addition to daily usage, I observe the dates when new models are launched, and for a select set of applications and models, their model specific weekly demand.

The analysis in this paper is descriptive. I zoom in on several model release events that happened in 2025, and document demand patterns around these release events. Specifically, I focus on the releases of Claude Sonnet 3.7, Gemini Flash 2.0, and Gemini Pro 2.5. For the analysis of multi-homing, I focus on two popular coding apps (Cline and Roo Code) and two popular chat apps (SillyTavern and Shapes Inc).

The facts documented above highlight a key tension in the demand for LLMs — how to reconcile persistent demand with seemingly low switching costs. For example, model providers such as Anthropic have achieved some level of demand stickiness despite not being cheap (Sonnet 3.7 is priced at \$3 per million tokens (MTok) while Gemini Pro 2.5 is priced at \$1.25 (MTok)) and not being at the top of benchmarks (for example Sonnet 3.7 (without thinking) scores 60.4% on the Aider polygot coding benchmark while Gemini Pro 2.5 scores 72.9%). A key question for competition is whether persistent demand reflects important differences in quality not measured by benchmarks. For example, maybe Claude has better 'vibes' than Gemini for coding. Alternatively, there could be other behavioral factors that cause model use persistence. For example, persistent demand may reflect branding or superior integration of the model with specific coding tools.

While this analysis is a first look at LLM demand, it does have many limitations. First, OpenRouter does not have data on consumer usage of LLMs through native apps such as ChatGPT. Second, some popular apps such as Cursor do not use OpenRouter (or at least do not publicly disclose their usage). As a result, my analysis is only looking at part of the market. Finally, OpenRouter API calls come disproportionately from apps used for programming or character personas, and as a result are not representative of LLM demand for other use cases.

My work contributes to ongoing work in the economics of AI. Eloundou et al. (2024) and Handa et al. (2025) consider the potential task level exposure to LLMs, while Acemoglu (2024) embeds AI into a task based macroeconomic model. Several papers have considered how AI can affect productivity for a variety of tasks (Brynjolfsson, Li, and Raymond (2025), Dell'Acqua et al. (2023), and Handa et al. (2025)). My work complements this work by considering the demand for better AI models.

Separately, a large literature in economics and marketing considers modeling demand (e.g., Dube (2019)). Of particular importance in demand modeling is the diversion ratio (Conlon and Mortimer (2021)), which is a measure of how demand shifts with changes to the availability or prices of products. I provide some of the first evidence of diversion ratios in the market for LLMs.

2 Institutional Background and Data Preparation

In this section, I first describe the data scraping and cleaning procedure used for the main dataset. I then describe the cleaned dataset.

OpenRouter is a private company that describes itself as "the unified interface for LLMs," with a subtitle of "Better prices, better uptime, no subscription." What this means in practice is that OpenRouter provides a standardized API for calling any of hundreds of models. This has a variety of advantages for developers in addition to simplicity. One advantage is that for models offered by several providers (e.g., gpt4o on Azure vs OpenAI), OpenRouter can smartly route the API call based on latency, price, or throughput. OpenRouter also gives developers options to use some models as fallback for others under specified circumstances.

On its site, OpenRouter provides a set of rankings that specify the top models by tokens used over time. Of particular interest is that the webpage for each model contains data on daily tokens used starting from January 11, 2025. The model page also includes other pertinent information such as price, uptime statistics, and top apps using the model per week (including tokens used). My main dataset comes from daily scrapes of these model pages, where there are 296 models in total.

From this dataset, I remove old models (those created before Jan 1, 2024) and I merge beta and non-beta versions of the same model. This leaves me at 249 models and 16,584 model day observations. Table 1 presents summary statistics at the model-day level. There is enormous variation in the demand for models, with some models not being used at all, while other models having prompt tokens on the order of 55 MTok per day (Anthropic's Claude Sonnet 3.7 has the highest average prompt token usage in the sample, while Google's Gemini Flash 2.0 has the highest average completion tokens). The number of tokens used for prompts is generally higher than the number of tokens used for completion. Context windows also vary quite a bit, with Google models generally having the largest context windows. Lastly, pricing is highly variable. OpenRouter hosts models that are free, but also hosts some of the most expensive models including Claude Sonnet 3.7 and OpenAI o1-pro.

Table 1: Summary Statistics by Model-Day

	Mean	Median	SD	Min	Max	N
Completion Tokens (M)	55.24	2.61	281.17	0.00	5069.85	16236
Prompt Tokens (M)	733.75	26.91	3911.66	0.00	55 130.95	16236
Context Window (M)	0.15	0.13	0.26	0.00	2.00	16236
Output Price per MTok	5.89	0.80	25.44	0.00	600.00	16236
Input Price per MTok	1.80	0.50	7.10	0.00	150.00	16236

Notes: Each observation is a model by day. MTok stands for million tokens.

Table A2 and Table A1 display these summary statistics broken out by model class (state-of-the-art (SOTA), fast & cheap, and old), and provider.[1] On average, Google models are much cheaper than Anthropic or OpenAI models, with other models being the cheapest. It is important to note that many of the other models are open source, smaller, and are served by a variety of providers such as Groq, Lambda, and DeepInfra.

Lastly, for data about specific applications and the models they use, I leverage the fact that OpenRouter reports the weekly top (public) apps using each model,[2] as well as the tokens used. By taking the union of these observations across models, I am able to compile app-specific model usage. This procedure isn't perfect, since I won't be able to see demand when an app is not in the top 20 for a particular model. That said, since the platform is dominated by a few models, and a few apps, I am able to obtain a detailed demand profile for top apps.

The top apps in my sample, along with their token usage are listed in Table 2. Three of the most used apps are for coding (Cline, Roo Code, and liteLLM). There are four apps that are useful for chat and/or personals (Shapes Inc, SillyTavern, Cub AI, and Chatroom). DocsLoop is an app used for data extraction from documents, Fraction AI is a platform for AI agents to compete, and Fish Audio is an audio AI provider.

[1]There isn't an obvious way to classify models, since their relative status changes over time. I defined state of the art as models that were at or close to the frontier of benchmarks at any point during the sample period. Table A3 displays all the models in the sample and my categorization.

[2]Not all apps allow OpenRouter to publicly display their usage data.

Table 2: Top Apps

Application	Usage (Millions of Tokens)
Cline	314583
Roo Code	231702
shapes inc	37620
SillyTavern	36883
Chub AI	17435
DocsLoop	14264
OpenRouter: Chatroom	13405
liteLLM	11461
Fraction AI	8085
Fish Audio	6445

Notes: Usage calculated for the models in which the app is in the top 20 public apps. This usage data comes from the week prior to April 11, 2025.

Lastly, it's helpful to consider the total usage of the platform and how it's evolving over time. The platform has shown consistent growth throughout the analysis period, as evidenced in Figure 1. Total revenue[3] increased from approximately $85K to over $200K per day between January and April 2025, though with significant volatility. Similarly, token usage has grown steadily from around 50 billion to over 250 billion tokens per day. This growth reflects both increased adoption of existing models and the introduction of new, more capable models during the period.

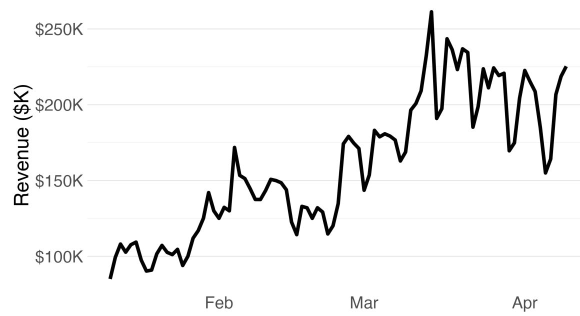
3 Case studies and stylized facts about LLM Demand

The bulk of the analysis consists of case studies, namely the demand patterns of models around the release of other models. I believe that this sort of analysis is informative since new model releases get a lot of media attention, offer new capabilities, and cause large shifts in demand.

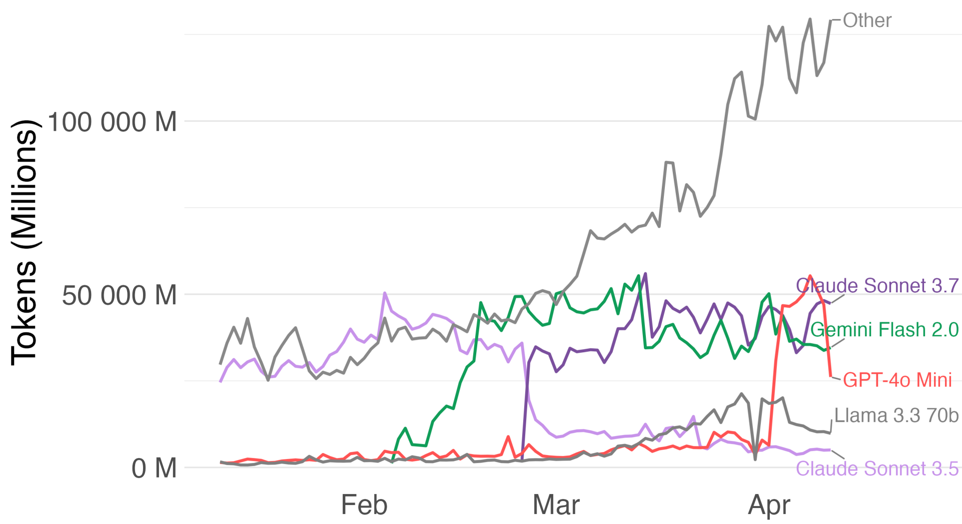
Nonetheless, it is useful to state the limitations of case study analysis. Formally, this interrupted time-series analysis requires many assumptions. Two I'd like to state explicitly are the following. First, there should be no concurrent events which occurred in the market in the same time period as the release of a model, which could have affected demand to a similar degree. This assumption might be violated if, for example, a large app started using OpenRouter in the same time period. Second, the release of a new model should not cause people to switch to using OpenRouter or away from using OpenRouter. These two assumptions need to be evaluated separately for each case study.

[3]Total revenue is calculated by using the price as of April 2025 for input and output tokens and multiplying it by the corresponding number of tokens. Reasoning tokens are not included in this calculation.

(a) Token Usage



(b) Revenue



(c) Top Models vs Other

Figure 1: OpenRouter Growth (Jan-Apr 2025)

3.1 Case Studies

Claude 3.7 Release: Claude Sonnet 3.7 is a frontier model that was released by Anthropic on Feb 24, 2025. The model was branded as having particular strengths in coding and front-end web development. Figure 2 shows the impact of Claude Sonnet 3.7's release on the token usage patterns of leading models (Figure A1 displays the results on a log scale). As a comparison, it plots demand for several other advanced models: Claude Sonnet 3.5, Anthropic's previous model, OpenAI's model GPT-4o and Deepseek.

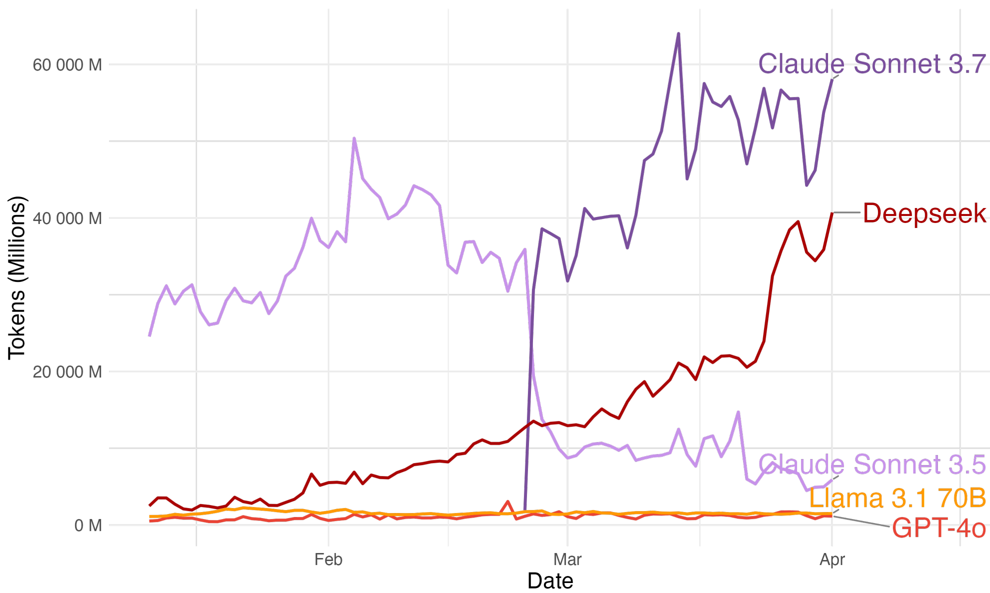
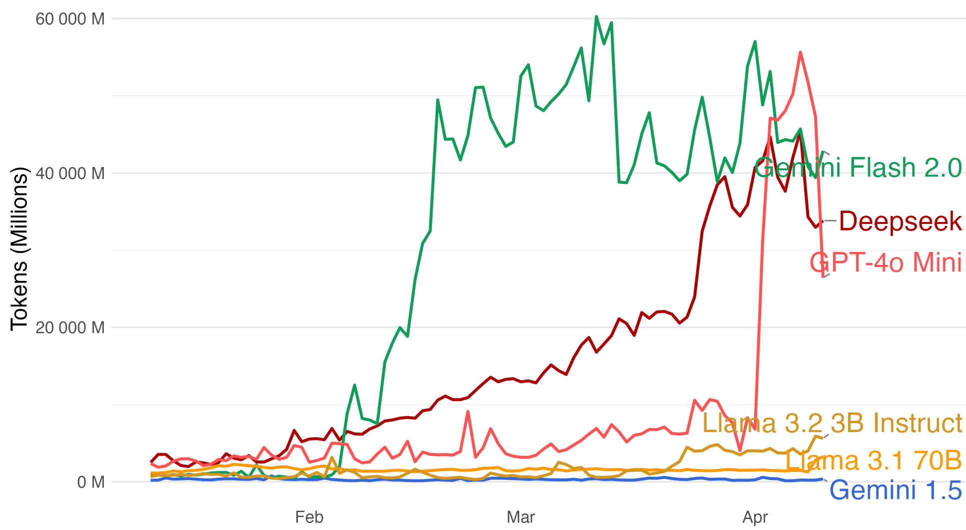


Figure 2: Token Usage for a Models Following Claude Sonnet 3.7 Release (Feb. 2025)

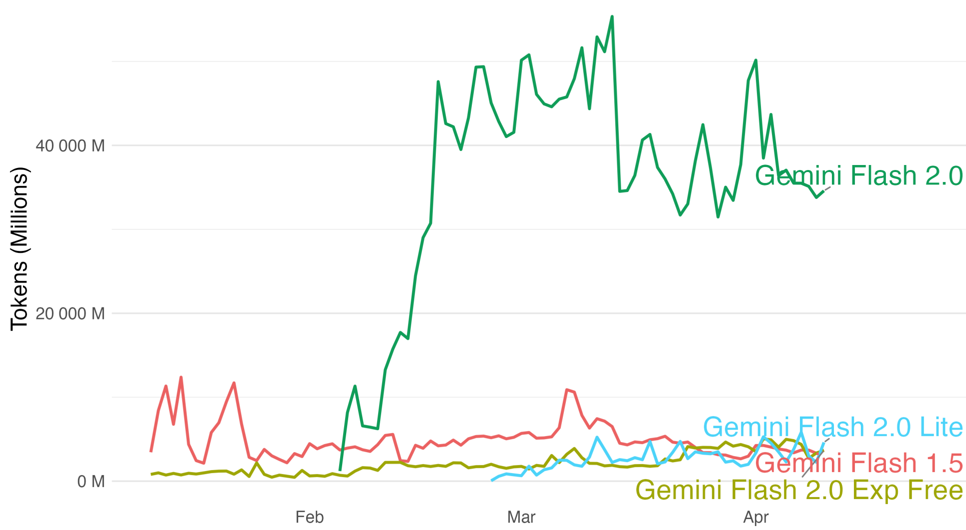
Gemini Flash 2.0 Release: Gemini Flash 2.0 was fully released by Google on February 05, 2025, in concurrence with the release of Gemini 2.0 Flash-Lite which is a more cost-efficient variant. Preview versions of this model were available to a limited extent on OpenRouter prior to this date. Gemini 2.0 is considered a strong and quick model for its price, even though it does not achieve state-of-the-art performance on capabilities benchmarks.

Figure 3a shows the demand for Gemini Flash 2.0 and other potentially comparable models including Deepseek, Gemini 1.5, GPT-4o mini and two Llama variants (Figure A3 displays the results on a log scale). Note, I aggregate three related Gemini Flash 2.0 models — Flash, Flash Experimental Free, and Flash Lite. We see a rapid rise in Gemini Flash 2.0 demand (green line) after its release. To help interpret the increase in demand, I plot the demand for related models separately (Figure 3b). The increase is driven by the main Gemini Flash 2.0 model and not by the variants.

Gemini 2.5 Pro Release: Gemini Pro 2.5 is Google DeepMind's first "thinking" Gemini model.[4] An experimental build shipped to Google AI Studio and Vertex AI on March 25 2025. OpenRouter began offering the free experimental variant a few days after the initial rollout, giving developers access to the model. This experimental version is rate limited for



(a) Token Usage for Models Following Gemini Flash 2.0 Release



(b) Disaggregated view of Gemini Flash models

Figure 3: Gemini Flash 2.0 Release (Feb. 2025)

developers, meaning that they couldn't use it fully. Gemini Pro 2.5 Preview was released later without these rate limits.

Figure 4 shows demand for Gemini 2.5 (teal) alongside other comparable models including Claude Sonnet 3.7, Gemini 2.0 Flash, Deepseek, and GPT-4o (Figure A2 displays the results on a log scale). Demand for Gemini Pro 2.5 rises quickly, but remains below that of Calude 3.7 Sonnet, Deepseek, and Gemini 2.0 Flash.

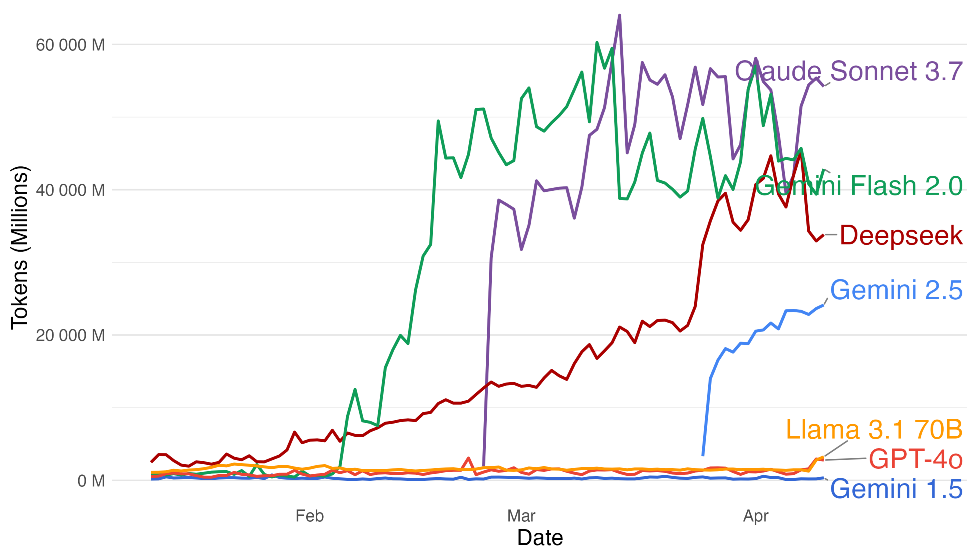


Figure 4: Token Usage for Models Following Gemini Flash 2.5 Release (March 2025)

3.2 Three facts about LLM Demand

Fact 1: The release of better models results in rapid adoption. Across all three case studies, adoption of the new model occurs quickly, with an initial jump in log tokens that stabilizes within a few weeks of a model's release on OpenRouter. This is true even when the model provider has not previously been known for frontier models. For example, Google's Gemini 2.5 was the first of its model to achieve the state-of-the-art performance on a variety of LLM benchmarks. Yet even though many may not have expected it to garner fast adoption, it did so relatively quickly. This fast adoption curve is also evident for fast and cheap models, such as Gemini 2.0 Flash.

Note that while the initial jump is rapid, growth in model usage can continue afterward. For example, usage of Gemini 2.5 continues to increase after the initial jump in demand, but at a slower rate. This continued growth of Gemini 2.5 is consistent with the overall growth of the OpenRouter platform, as well as with ongoing learning and optimization by users of the LLMs.

[4] Thinking or reasoning models are trained to use output tokens to consider their answer prior to answering a prompt.

Fact 2: New model releases differ in the degree to which they cause substitution from existing models or expand the market. For each of the three case studies, I picked comparison models that would ex-ante potentially be strong competitors. If models are substitutes, we would expect to see that demand for these models falls as the new model is adopted. We see quite different trends across the three releases, with some models expanding the market and other models creating obvious substitution.

First, consider the release of Claude Sonnet 3.7 (Figure 2). We see an obvious decline in the usage of Claude 3.5 Sonnet that is concurrent with the adoption of 3.7. Yet, we see no obvious movement in potentially competitive models such as DeepSeek, GPT-4o, and Llama 3.1 70B. My interpretation of this is that substitution for Claude comes mainly within model class (Claude Sonnet), and not from other models. This within Claude Sonnet substitution may be due to a variety of factors. For example, the set of users who are willing to pay for the best coding LLM may have been primarily using Sonnet 3.5 and naturally found it easy to switch to Sonnet 3.7. Alternatively, there may be an Anthropic or Sonnet brand effect that is strong for a subset of users.

Second, consider the release of Gemini Flash 2.0 (Figure 3a). This figure includes several comparison models, including Gemini Flash 1.5 and Llama, that might ostensibly be considered either cheap or fast, just like Gemini 2.0 Flash. Yet none of these models experience a drop in demand that is concurrent with the rise of Gemini 2.0 Flash. In fact, demand for Gemini 2.0 quickly rises to be greater than the demand for all the other models. One way to interpret this is that Gemini 2.0 greatly expanded the market for LLMs.

Lastly, consider the release of Gemini 2.5 (Figure 4. I observe rapid adoption of the model, but that demand for other models did not seem to change in an obvious way concurrent with the release. This is once again evidence for a market expansion effect of certain LLMs. Of course, since this version of Gemini 2.5 was free and rate limited, we will have to wait to get more data on the full release to learn more about the long-run effects of Gemini 2.5's release.

Fact 3: There is substantial multi-homing. The same app uses a mix of available models. The final fact I'd like to document is that there is substantial multi-homing in LLM use. In particular, the same app typically uses a mix of models. To see this, I focus on two popular programming apps (Cline and Roo Code) and two popular chat and persona apps (Shapes Inc and SillyTavern).

Figure 5 shows the tokens used by model for Cline and Roo Code. Both coding apps have a mix of models used. Claude Sonnet 3.7 is the most popular for both apps, but Gemini Pro 2.5 is a strong second contender. In addition, Deepseek, Claude Sonnet 3.5, and Optimus Alpha (an early version of Gpt4.1) all saw substantial usage. This data shows that users don't perceive just one model to be the best for coding.

Figure 6 shows similar multi-homing for SillyTavern and Shapes Incs. Both apps have a variety of models used. SillyTavern has the greatest usage for DeepSeek and Claude, with a substantial share of other models in the long tail (yellow bar). Shapes Inc has quite a different pattern with a max of mainly Gemini Flash 2.0 and Llama 3.1 8b. The overall pattern for Shapes Inc suggests a preference for cheap and fast models. Even within these

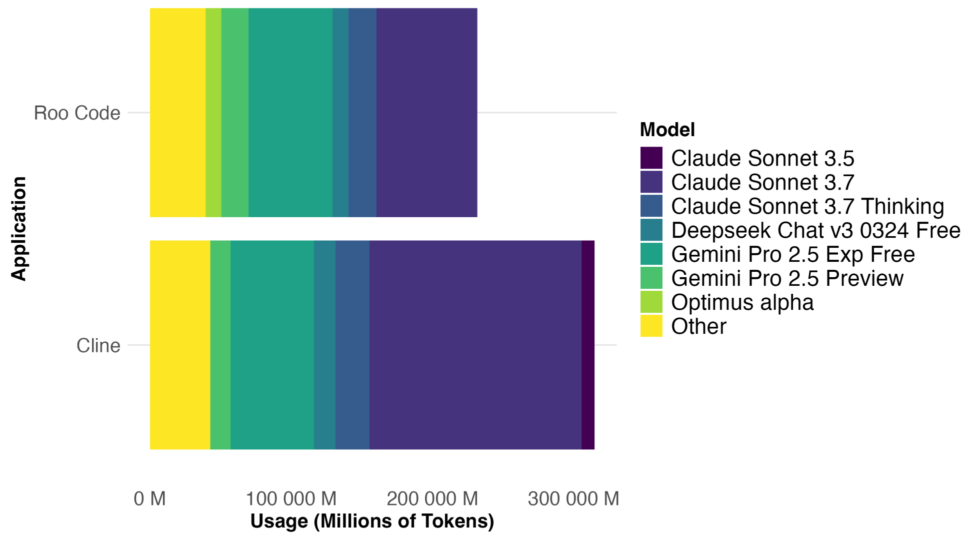


Figure 5: Tokens Used by Model and App (Coding)

models, however, there is a lot of variety with a concentration in Llama and Gemini 2.0 Flash.

To summarize, there is a large degree of multi-homing in four popular apps using LLMs.[5] Multi-homing is prevalent, and each app tends to use different combinations of LLMs.

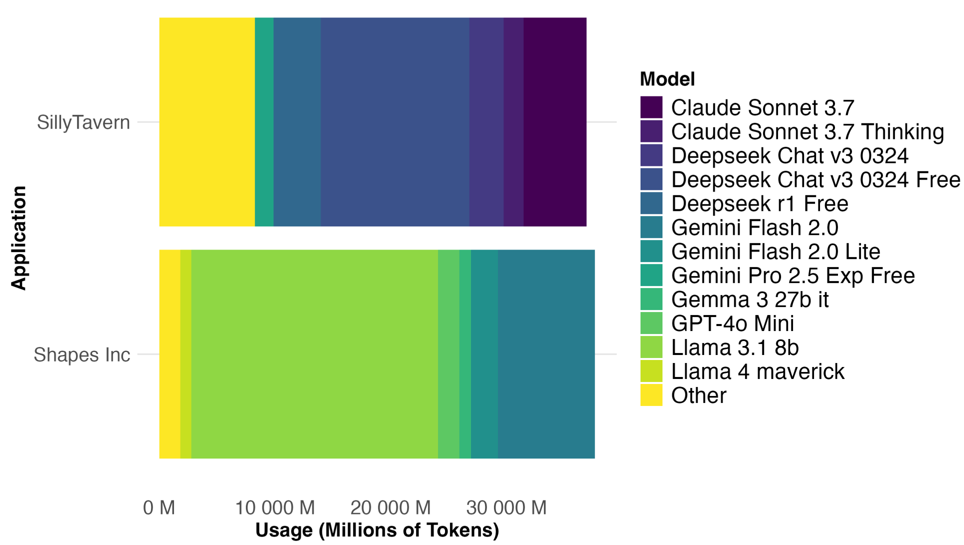


Figure 6: Tokens Used by Model and App (Chat and Personas)

[5]Data on multihoming is harder to obtain for less popular apps, since OpenRouter only reports the top

4 Implications for competition in AI and open questions.

It is useful to think of competition in LLMs through the lens of industrial organization economics. In a standard static Bertrand-Nash pricing equilibrium, firms are able to earn profits when their product is differentiated from other products or when some firms have cost advantages over other firms. In my analysis I've focused on the demand side of the market, ignoring the cost side.

In markets where products are differentiated from each other, higher priced products are able to garner substantial demand. We see that this is indeed the case, with Claude Sonnet 3.7 being relatively expensive and having high demand. Differentiation is typically modeled in a vertical dimension (there is one dimension of quality which everyone agrees upon) and a horizontal dimension (in which some people prefer one model while others prefer another at the same price).

For the LLM market, the existence of horizontal differentiation is particularly important. The reason for this is that smarter and more capable models are released many times a year, and no one provider can hope to always offer the most capable model. In contrast, if models are horizontally differentiated, then providers who don't offer the most capable model can still garner substantial demand with a price markup.

The three stylized facts suggest that demand for LLMs is differentiated horizontally in addition to vertically. New models are adopted quickly, but substitution patterns differ greatly across models. Sonnet models seem to be substitutes for each other but not for other models. In contrast, Gemini Flash 2.0 and Pro 2.5 expand the market for LLMs without any obvious cannibalization effects. If the most capable models at a given price point received all the demand, we would see a lot more substitution and one model dominating every price point. Additionally, the presence of LLM multi-homing across four popular apps suggests that different LLMs have different use cases for serving end-users.

This work is meant to offer an initial look at LLM demand, but many open questions remain. The first, and perhaps the most obvious, question is how demand for LLMs responds to price. In order to learn about this, we would need to observe price changes within a model. Even then, there may be differences between short-run price elasticities (responses of demand to short-run pricing changes) and long-run price elasticities (responses of demand to sustained price reductions as computing capacity increases).

A second question concerns the dimensions of horizontal differentiation in the LLM market. Some obvious ones include speed, context window, down-time, throughput, and license terms. Others include more subjective perceptions such as 'vibes' and the presence of app-model integration (when for example a coding tool is optimized to use one LLM and not another). Relatedly, capacity constraints may play an important role in this market, and may limit the extent to which one model provider can capture the market.

Lastly, OpenRouter is just one marketplace for LLMs, and does not see the entire market.

20 apps per model. Figure A5 displays tracked model usage for four other apps, three of which display substantial multihoming.

It remains an open question whether users that directly interface with model providers such as Anthropic, Google, and OpenAI exhibit similar demand patterns.

References

Acemoglu, Daron. 2024. "The Simple Macroeconomics of AI." w32487, National Bureau of Economic Research.

Brynjolfsson, Erik, Danielle Li, and Lindsey Raymond. 2025. "Generative AI at work." *The Quarterly Journal of Economics*: qjae044.

Conlon, Christopher, and Julie Holland Mortimer. 2021. "Empirical properties of diversion ratios." *The RAND Journal of Economics* 52 (4): 693–726.

Dell'Acqua, Fabrizio, Raj Agarwal, Marco Iansiti, and Shi Zheng. 2023. "Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality." 24-013, Harvard Business School Technology & Operations Mgt. Unit Working Paper.

Dube, Jean-Pierre. 2019. "Microeconometric models of consumer demand." In *Handbook of the Economics of Marketing*, edited by Jean-Pierre Dube and Peter E Rossi, vol. 1, chap. 1, 1–68.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock. 2024. "GPTs are GPTs: Labor market impact potential of LLMs." *Science* 384 (6702): 1306–1308.

Handa, Kunal, Tyna Eloundou, Anand Thakkar, Richard Mansfield, and Daniel Rock. 2025. "Which Economic Tasks are Performed with AI? Evidence from Millions of Claude Conversations." *arXiv preprint arXiv:2503.04761*.

A Addition Figures

A.1 Claude Sonnet 3.7 Release

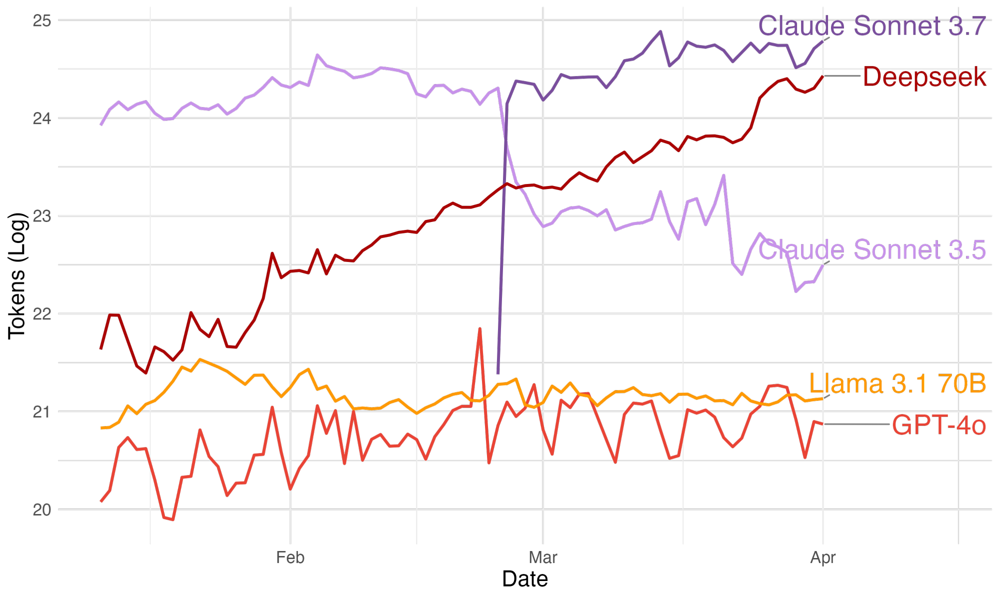


Figure A1: Claude Sonnet 3.7 Release Comparison (Log Scale)

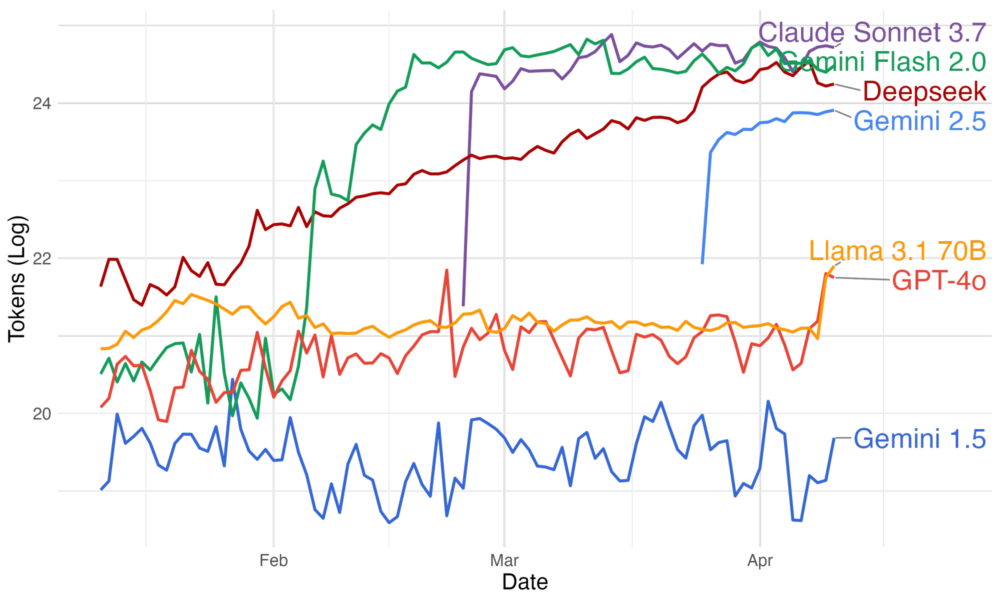


Figure A2: Gemini 2.5 Pro Release Comparison (Log Scale)

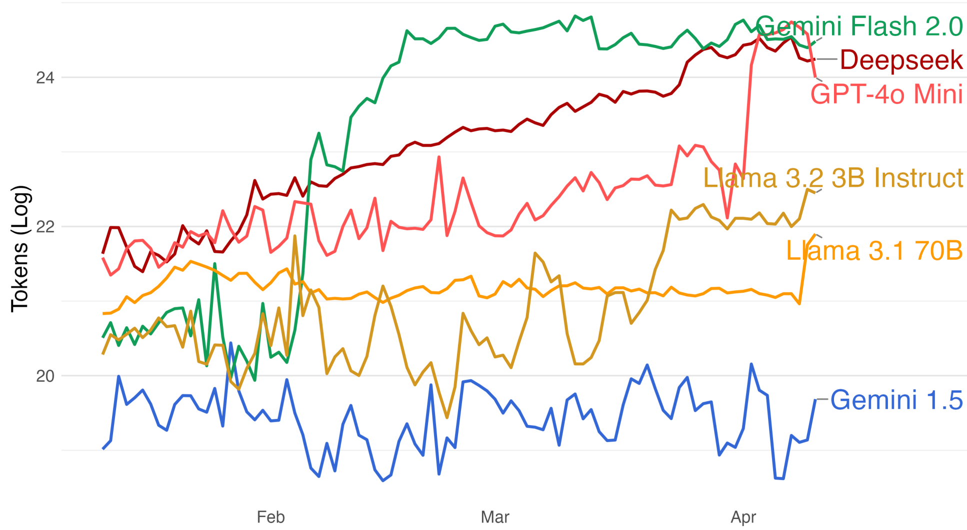


Figure A3: Gemini Flash 2.0 Release Comparison (Log Scale)

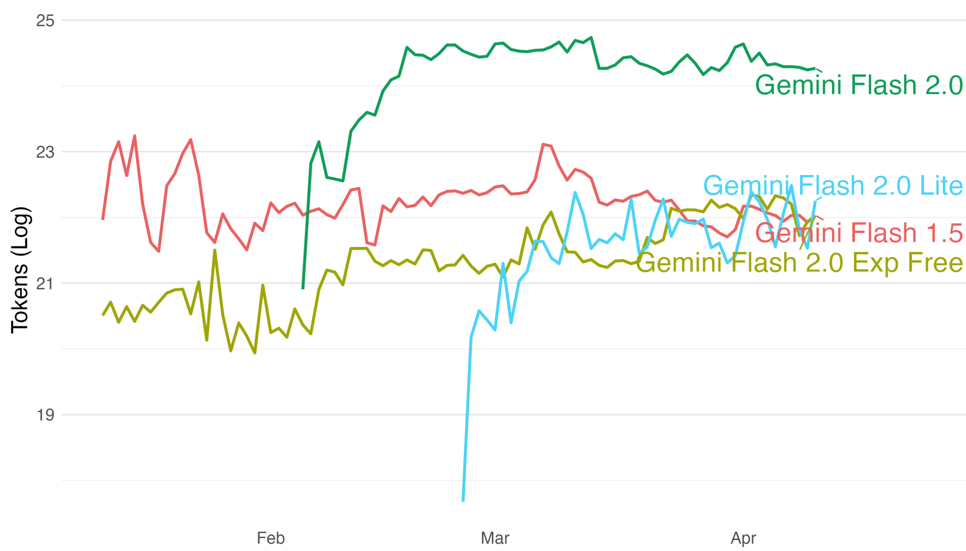


Figure A4: All Gemini 2.0 Models Usage (Log Scale)

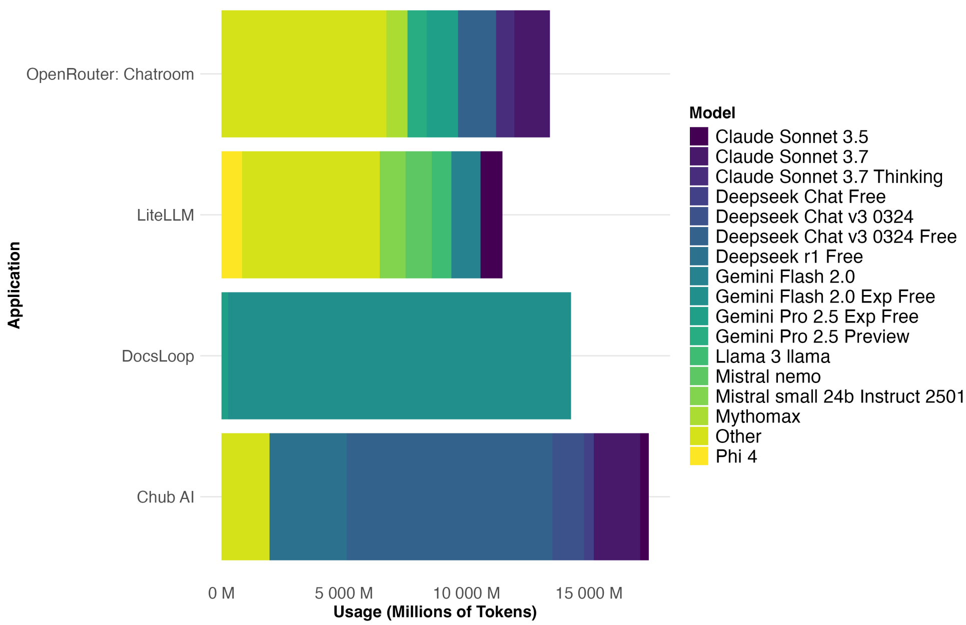


Figure A5: Tracked Model Usage for Other Apps

B Additional Tables

Table A1: Summary Statistics by Provider

Provider		Mean	Median	SD
Anthropic	Completion Tokens (M)	68.94	3.28	170.16
	Prompt Tokens (M)	3885.71	69.86	10 448.85
	Context Window (M)	0.20	0.20	0.00
	Output Price per MTok	19.04	15.00	25.60
	Input Price per MTok	3.81	3.00	5.12
Google	Completion Tokens (M)	288.80	12.34	801.77
	Prompt Tokens (M)	2845.18	156.36	7833.41
	Context Window (M)	0.69	1.00	0.59
	Output Price per MTok	0.53	0.00	1.44
	Input Price per MTok	0.17	0.00	0.37
OpenAI	Completion Tokens (M)	48.68	4.79	168.81
	Prompt Tokens (M)	518.27	24.42	3317.77
	Context Window (M)	0.13	0.13	0.04
	Output Price per MTok	29.33	10.00	70.11
	Input Price per MTok	8.79	2.50	19.94
Other	Completion Tokens (M)	30.30	2.10	157.13
	Prompt Tokens (M)	261.11	19.25	1065.70
	Context Window (M)	0.10	0.07	0.13
	Output Price per MTok	2.04	0.60	3.47
	Input Price per MTok	0.83	0.25	1.12

Notes: Each observation is a model by day. MTok stands for million tokens.

Table A2: Summary Statistics by Class

Model Class		Mean	Median	Max
SOTA	Completion Tokens (M)	125.70	26.34	4418.45
	Prompt Tokens (M)	1918.66	215.68	55 130.95
	Context Window (M)	0.22	0.13	2.00
	Output Price per MTok	18.17	0.90	600.00
	Input Price per MTok	5.33	0.50	150.00
Fast & Cheap	Completion Tokens (M)	89.35	3.50	5069.85
	Prompt Tokens (M)	856.20	44.87	53 810.14
	Context Window (M)	0.21	0.13	1.05
	Output Price per MTok	0.64	0.15	4.40
	Input Price per MTok	0.20	0.09	1.10
Old	Completion Tokens (M)	36.67	1.71	623.47
	Prompt Tokens (M)	2412.09	29.22	49 803.12
	Context Window (M)	0.17	0.20	0.20
	Output Price per MTok	31.11	15.00	75.00
	Input Price per MTok	7.39	5.00	15.00

Notes: Each observation is a model by day. MTok stands for million tokens.

Table A3: List of All Models Used in Analysis

Model Name	Provider	Model Class
01 ai yi large	01-Ai	Other
Aetherwiing mn starcannon 12b	Aetherwiing	Other
Ai21 jamba 1 5 Mini	Ai21	Fast & Cheap
Ai21 jamba 1 5 large	Ai21	Other
Ai21 jamba 1.6 Mini	Ai21	Fast & Cheap
Ai21 jamba 1.6 large	Ai21	Other
Ai21 jamba Instruct	Ai21	Other
Aion 1.0	Aion-Labs	Other
Aion 1.0 Mini	Aion-Labs	Fast & Cheap
Llama rp llama	Aion-Labs	Fast & Cheap
Openhands lm 32b v0.1	All-Hands	Other
Molmo 7b d Free	Allenai	Fast & Cheap
Olmo 2 0325 32b Instruct	Allenai	Other
Magnum 72b	Alpindale	Other
Amazon nova Pro v1	Amazon	Other
Amazon nova lite v1	Amazon	Other
Amazon nova micro v1	Amazon	Other
Anthracite org magnum v2 72b	Anthracite-Org	Other
Anthracite org magnum v4 72b	Anthracite-Org	Other
Claude 3 Haiku	Anthropic	Fast & Cheap
Claude 3 Haiku beta	Anthropic	Fast & Cheap
Claude 3 Opus	Anthropic	Old
Claude 3 Opus beta	Anthropic	Old
Claude 3 Sonnet	Anthropic	Old
Claude 3 Sonnet beta	Anthropic	Old
Claude Haiku 3.5	Anthropic	Fast & Cheap
Claude Sonnet 3.5	Anthropic	Old
Claude Sonnet 3.7	Anthropic	SOTA
Claude Sonnet 3.7 Thinking	Anthropic	SOTA
Ui tars 72b Free	Bytedance-Research	Other
Dolphin mixtral 8x22b	Cognitivecomputations	Other
Dolphin3.0 mistral 24b Free	Cognitivecomputations	Other
Dolphin3.0 r1 mistral 24b Free	Cognitivecomputations	Other
Command	Cohere	Other
Command a	Cohere	Other
Command r	Cohere	Other
Command r 03 2024	Cohere	Other
Command r 08 2024	Cohere	Other

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Model Name	Provider	Model Class
Command r Plus	Cohere	Other
Command r Plus 04 2024	Cohere	Other
Command r Plus 08 2024	Cohere	Other
Command r7b 12 2024	Cohere	Fast & Cheap
Deepseek Chat	Deepseek	SOTA
Deepseek Chat Free	Deepseek	SOTA
Deepseek Chat v3 0324	Deepseek	SOTA
Deepseek Chat v3 0324 Free	Deepseek	SOTA
Deepseek r1	Deepseek	SOTA
Deepseek r1 Free	Deepseek	SOTA
Deepseek r1 distill llama 70b	Deepseek	SOTA
Deepseek r1 distill llama 70b Free	Deepseek	SOTA
Deepseek r1 distill llama 8b	Deepseek	Fast & Cheap
Deepseek r1 distill qwen 1.5b	Deepseek	Fast & Cheap
Deepseek r1 distill qwen 14b	Deepseek	Fast & Cheap
Deepseek r1 distill qwen 14b Free	Deepseek	Fast & Cheap
Deepseek r1 distill qwen 32b	Deepseek	SOTA
Deepseek r1 distill qwen 32b Free	Deepseek	SOTA
Deepseek r1 zero Free	Deepseek	SOTA
Deepseek v3 base Free	Deepseek	SOTA
Eva qwen 2.5 32b	Eva-Unit-01	Other
Eva qwen 2.5 72b	Eva-Unit-01	Other
Llama llama 3.33	Eva-Unit-01	Other
Qwerky 72b Free	Featherless	Other
Gemini Flash 1.5	Google	Fast & Cheap
Gemini Flash 1.5 8B	Google	Fast & Cheap
Gemini Flash 1.5 Exp 8B	Google	Fast & Cheap
Gemini Flash 2.0	Google	Fast & Cheap
Gemini Flash 2.0 Exp Free	Google	Fast & Cheap
Gemini Flash 2.0 Lite	Google	Fast & Cheap
Gemini Flash 2.0 Thinking Free	Google	Fast & Cheap
Gemini Pro 1.5	Google	SOTA
Gemini Pro 2.5 Exp Free	Google	SOTA
Gemini Pro 2.5 Preview	Google	SOTA
Gemma 2 27b it	Google	Fast & Cheap
Gemma 2 9b it	Google	Fast & Cheap
Gemma 2 9b it Free	Google	Fast & Cheap
Gemma 3 12b it	Google	Fast & Cheap
Gemma 3 12b it Free	Google	Fast & Cheap

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Model Name	Provider	Model Class
Gemma 3 1b it Free	Google	Fast & Cheap
Gemma 3 27b it	Google	Fast & Cheap
Gemma 3 27b it Free	Google	Fast & Cheap
Gemma 3 4b it	Google	Fast & Cheap
Gemma 3 4b it Free	Google	Fast & Cheap
Learnlm 1.5 Pro experimental Free	Google	Other
Infermatic mn inferor 12b	Infermatic	Other
Inflection 3 pi	Inflection	Other
Inflection 3 productivity	Inflection	Other
Llama large 70b	Latitudegames	Other
Lfm 3b	Liquid	Fast & Cheap
Lfm 40b	Liquid	Other
Lfm 7b	Liquid	Fast & Cheap
Llama 3 70b Instruct	Meta-Llama	SOTA
Llama 3 8b Instruct	Meta-Llama	Fast & Cheap
Llama 3.1 405b	Meta-Llama	Other
Llama 3.1 70b	Meta-Llama	SOTA
Llama 3.1 8b	Meta-Llama	Fast & Cheap
Llama 3.2 11b	Meta-Llama	Other
Llama 3.2 1b	Meta-Llama	Other
Llama 3.2 3b	Meta-Llama	Fast & Cheap
Llama 3.2 90b	Meta-Llama	Other
Llama 3.3 70b	Meta-Llama	SOTA
Llama 4 maverick	Meta-Llama	Other
Llama 4 maverick Free	Meta-Llama	Other
Llama 4 scout	Meta-Llama	Other
Llama 4 scout Free	Meta-Llama	Other
Llama guard 2 8b	Meta-Llama	Fast & Cheap
Llama guard 3 8b	Meta-Llama	Fast & Cheap
Phi 3 Mini 128k Instruct	Microsoft	Fast & Cheap
Phi 3 medium 128k Instruct	Microsoft	Other
Phi 3.5 Mini 128k Instruct	Microsoft	Fast & Cheap
Phi 4	Microsoft	Other
Phi 4 multimodal Instruct	Microsoft	Other
Wizardlm 2 7b	Microsoft	Fast & Cheap
Wizardlm 2 8x22b	Microsoft	SOTA
Minimax 01	Minimax	Fast & Cheap
Mistral ministral 8b	Mistral	Fast & Cheap
Codestral 2501	Mistralai	SOTA

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Model Name	Provider	Model Class
Codestral Mamba	Mistralai	SOTA
Ministral 3b	Mistralai	Fast & Cheap
Ministral 8b	Mistralai	Fast & Cheap
Mistral large	Mistralai	Other
Mistral large 2407	Mistralai	Other
Mistral large 2411	Mistralai	Other
Mistral medium	Mistralai	Other
Mistral nemo	Mistralai	Fast & Cheap
Mistral nemo Free	Mistralai	Fast & Cheap
Mistral saba	Mistralai	Other
Mistral small	Mistralai	Fast & Cheap
Mistral small 24b Instruct 2501	Mistralai	Fast & Cheap
Mistral small 24b Instruct 2501 Free	Mistralai	Fast & Cheap
Mistral small 3.1 24b Instruct	Mistralai	Fast & Cheap
Mistral small 3.1 24b Instruct Free	Mistralai	Fast & Cheap
Mistral tiny	Mistralai	Fast & Cheap
Mixtral 8x22b Instruct	Mistralai	Other
Pixtral 12b	Mistralai	Other
Pixtral large 2411	Mistralai	Other
Kimi vl a3b thinking Free	Moonshotai	Fast & Cheap
Moonlight 16b a3b Instruct Free	Moonshotai	Fast & Cheap
Llama 3 lumimaid 70b	Neversleep	Other
Llama 3 lumimaid 8b	Neversleep	Fast & Cheap
Llama 3 lumimaid 8b extended	Neversleep	Fast & Cheap
Llama 3.1 lumimaid	Neversleep	Other
Llama 3.1 lumimaid	Neversleep	Fast & Cheap
Nothingiisreal mn celeste 12b	Nothingiisreal	Other
Deephermes 3 llama 3 8b Preview Free	Nousresearch	Fast & Cheap
Hermes 2 Pro llama 3 8b	Nousresearch	Fast & Cheap
Llama 3 llama	Nousresearch	Other
Llama 3 llama	Nousresearch	SOTA
Nous hermes 2 mixtral 8x7b dpo	Nousresearch	Fast & Cheap
Llama llama 3.1	Nvidia	Fast & Cheap
Llama llama 3.3	Nvidia	Fast & Cheap
Olympiccoder 32b Free	Open-R1	Other
Olympiccoder 7b Free	Open-R1	Fast & Cheap
ChatGPT-4o latest	Openai	SOTA
GPT-3.5 Turbo 0613	Openai	Other
GPT-4 Turbo	Openai	Old

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Model Name	Provider	Model Class
GPT-4 Turbo Preview	Openai	Old
GPT-4.5 Preview	Openai	SOTA
GPT-4o	Openai	SOTA
GPT-4o 2024 05 13	Openai	Old
GPT-4o 2024 08 06	Openai	Old
GPT-4o 2024 11 20	Openai	SOTA
GPT-4o Mini	Openai	Fast & Cheap
GPT-4o Mini 2024 07 18	Openai	Fast & Cheap
GPT-4o Mini search Preview	Openai	Fast & Cheap
GPT-4o extended	Openai	SOTA
GPT-4o search Preview	Openai	SOTA
O1	Openai	SOTA
O1 Mini	Openai	Fast & Cheap
O1 Mini 2024 09 12	Openai	Fast & Cheap
O1 Preview	Openai	SOTA
O1 Preview 2024 09 12	Openai	SOTA
O1 Pro	Openai	SOTA
O3 Mini	Openai	SOTA
O3 Mini high	Openai	SOTA
Optimus alpha	Openrouter	Other
Llama 3.1 sonar	Perplexity	Other
R1 1776	Perplexity	Other
Sonar	Perplexity	Other
Sonar Pro	Perplexity	Other
Sonar deep research	Perplexity	Other
Sonar reasoning	Perplexity	Other
Sonar reasoning Pro	Perplexity	Other
Qwen 2 72b Instruct	Qwen	Other
Qwen 2.5 72b Instruct	Qwen	Other
Qwen 2.5 72b Instruct Free	Qwen	Other
Qwen 2.5 7b Instruct	Qwen	Fast & Cheap
Qwen 2.5 7b Instruct Free	Qwen	Fast & Cheap
Qwen 2.5 coder 32b Instruct	Qwen	Other
Qwen 2.5 coder 32b Instruct Free	Qwen	Other
Qwen 2.5 vl 72b Instruct	Qwen	Other
Qwen 2.5 vl 7b Instruct	Qwen	Fast & Cheap
Qwen 2.5 vl 7b Instruct Free	Qwen	Fast & Cheap
Qwen Plus	Qwen	Other
Qwen Turbo	Qwen	Other

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Model Name	Provider	Model Class
Qwen max	Qwen	Other
Qwen vl Plus	Qwen	Other
Qwen vl max	Qwen	Other
Qwen2.5 32b Instruct	Qwen	Other
Qwen2.5 vl 32b Instruct	Qwen	Other
Qwen2.5 vl 32b Instruct Free	Qwen	Other
Qwen2.5 vl 3b Instruct Free	Qwen	Fast & Cheap
Qwen2.5 vl 72b Instruct	Qwen	Other
Qwen2.5 vl 72b Instruct Free	Qwen	Other
Qwq 32b	Qwen	Other
Qwq 32b Free	Qwen	Other
Qwq 32b Preview	Qwen	Other
Qwq 32b Preview Free	Qwen	Other
Sorcererlm 8x22b	Raifle	Other
Reka Flash 3 Free	Rekaai	Fast & Cheap
Fimbulvetr 11b v2	Sao10k	Other
L3 euryale 70b	Sao10k	Other
L3 lunaris 8b	Sao10k	Fast & Cheap
L3.1 70b hanami x1	Sao10k	Other
L3.1 euryale 70b	Sao10k	Other
L3.3 euryale 70b	Sao10k	Other
Llama3.1 typhoon2 70b Instruct	Scb10x	Other
Llama3.1 typhoon2 8b Instruct	Scb10x	Fast & Cheap
Midnight rose 70b	Sophosympatheia	Other
Rogue rose 103b v0.2 Free	Sophosympatheia	Fast & Cheap
L3.3 electra r1 70b	Steelskull	Other
Anubis Pro 105b v1	Thedrummer	Fast & Cheap
Rocinante 12b	Thedrummer	Other
Skyfall 36b v2	Thedrummer	Other
Unslopnemo 12b	Thedrummer	Fast & Cheap
Llama 3.1 swallow	Tokyotech-Llm	Other
Llama 3.1 swallow	Tokyotech-Llm	Fast & Cheap
Grok 2 1212	X-Ai	Other
Grok 2 Vision 1212	X-Ai	Other
Grok 3 Mini beta	X-Ai	Fast & Cheap
Grok 3 beta	X-Ai	SOTA
Grok Vision beta	X-Ai	Other
Grok beta	X-Ai	Other