HuggingGraph: Understanding the Supply Chain of LLM Ecosystem

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Abstract

Large language models (LLMs) leverage deep learning architectures to process and predict sequences of words based on context, enabling them to perform a wide range of natural language processing tasks, such as translation, summarization, question answering, and content generation. However, the increasing size and complexity of developing, training, and deploying cutting-edge LLMs demand extensive computational resources and large-scale datasets. This creates a significant barrier for researchers and practitioners. Because of that, platforms that host models and datasets have gained widespread popularity. For example, on one of the most popular platforms, i.e., Hugging Face, there are more than 1.8 million models and more than 450K datasets by the end of June 2025, and the trend does not show any slowdown.

As existing LLMs are often built from base models or other pre-trained models and use external datasets, they can inevitably inherit vulnerabilities, biases, or malicious components that exist in previous models or datasets. Therefore, it is critical to understand these components' origin and development process to detect potential risks better, improve model fairness, and ensure compliance with regulatory frameworks. Motivated by that, this project aims to study such relationships between models and datasets, which are the central parts of the *LLM supply chain*. First, we design a methodology to collect LLMs' supply chain information systematically. With the collected information, we design a new graph to model the relationships between models and datasets, which is a large directed heterogeneous graph, having *402,654 nodes* and *462,524 edges*. Then, on top of this graph, we perform different types of analysis and make multiple interesting findings.

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1 Introduction

Large language models (LLMs) are AI models designed to understand and generate human language by learning patterns and relationships within extensive datasets [33, 40], such as GPT (Generative Pre-trained Transformer) [54], BERT (Bidirectional Encoder Representations from Transformers) [24], and T5 (Text-To-Text Transfer Transformer) [5]. These models leverage deep learning architectures to process and predict sequences of words based on context, enabling them to perform a wide range of natural language processing tasks [7], such as, translation [30], summarization [27], question-answering [3], and content generation [1]. LLMs usually have billions (or even trillions) of parameters [31], enabling them to generate high-quality text.

However, the increasing size and complexity of developing, training, and deploying cutting-edge LLMs demand extensive computational resources [52] and large-scale datasets [49]. This creates a significant barrier for researchers and practitioners, limiting their access to state-of-the-art models [34]. As the demand for democratizing access to such LLM models continues to rise, platforms that host models and datasets have gained widespread popularity. For example, Figure 1 shows the number of models and datasets (in a million scales) on Hugging Face, the largest public AI model hosting platform [14], starting from July 2024 to June 2025. By the end of June 2025, it has reached over 1.8M models and 450K datasets. In addition, the trend does not show any slowdown. Such LLM hosting platforms provide user-friendly interfaces, APIs, and cloud-based infrastructures that enable researchers and developers to easily share, fine-tune, and deploy models without requiring extensive computational resources. Moreover, they foster open collaboration, allowing the broader community to contribute to model improvements, benchmark performances, and enhance transparency in AI research.

On such platforms, different types of models can be classified into two categories based on their tasks, i.e., *base models* and *task-specific models*. (i) *Base models* are large, pre-trained models that can be fine-tuned for specific downstream tasks [44]. They are usually trained on vast datasets and are general-purpose, such as GPT [54], BERT [24], and T5 [5]. (ii) *Task-specific models* are modified versions of base models for a specific task. Taking Hugging Face as an example, there are four types of such models. First, *fine-tuned models* adapt base models for specific tasks by training on additional task-specific datasets [55]. Second, *adapters models* add lightweight and modular layers to the pre-trained models for specific tasks [20]. Third, *quantization models* trade off precision in numerical computations for accelerating inference and reducing memory consumption (e.g., using less precise model parameters) [48]. Fourth, *merged models* integrate multiple models into a single unified model by combining weights or configurations enabling support for multiple tasks or domains without separate deployments [2]. Besides models, such platforms also host many *datasets* used for training and fine-tuning the previously discussed models [39].

1.1 Motivation

As existing LLMs are often built from base models or other pre-trained models and using external datasets, they can inevitably inherit vulnerabilities, biases, or malicious components from previous models or datasets. Thus, *understanding these components' origin and*

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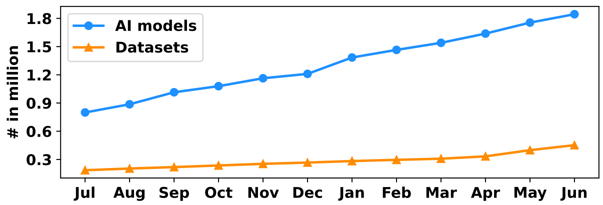


Figure 1: The number of AI models and datasets (in a million scale) on Hugging Face from July 2024 to June 2025.

provenance can help better detect potential risks, improve model fairness, and ensure compliance with regulatory frameworks.

Motivated by that, this paper aims to study such relationships between models and datasets. They are the central parts of the *LLM supply chain* [51], which refers to the entire lifecycle of developing, training, and deploying LLMs, similar to a traditional supply chain in manufacturing or software development [4, 9, 43, 56]. Such a supply chain can help to identify critical insights for both model evolution and dataset origin, as discussed below.

Model evolution. The study of the LLM supply chain gives a clear overview of how LLMs evolve from base models to fine-tuned variants, adapter integration, and quantization models. With that, one can easily keep track of them. For example, a use case is when a security vulnerability is found in one LLM, and we can quickly locate the potential models that might have the same issues.

Dataset origin. This supply chain can also help to understand the datasets' origins used for training different models [40]. Dataset origin refers to the source from which the data is collected. For example, for a fine-tuned model, we not only care about which dataset is used for fine-tuning but also what other datasets are involved in training the previous model. Understanding such dataset origin helps to ensure that the dataset used is reliable, and legally compliant.

1.2 Contribution

Our main contributions are threefold. First, we design a methodology to systematically collect the supply chain information of LLMs. In this paper, we mainly study the most popular AI platform, i.e., Hugging Face, but the same strategy applies to other platforms. In particular, we use the APIs from the AI platform to collect the metadata about the hosted model and dataset. To this end, we collected a large dataset as of *June 30, 2025*.

Second, with the collected metadata, we created a new graph, named ***LLM supply chain graph***, to model the relationships between models and datasets. It is a directed heterogeneous graph where a node denotes different types of datasets and models (including base, fine-tune, adapter, quantization, and merge). An edge denotes the dependency relationship between them, including model-model, dataset-dataset, and model-dataset relationships. Together, this graph is able to accurately capture the LLM supply chain information. To this end, we constructed a large graph with **402,654 nodes** and **462,524 edges**. An anonymized version of the complete graph is publicly available at GitHub[1].

Third, with this graph, we perform different types of analysis, including forward and backward analysis. We study seven research questions, including (i) the properties of the LLM supply chain graph, (ii) structural analysis, (iii) supply chain relationships between AI models, (iv) supply chain relationships between datasets, (v) supply chain relationships between models and datasets, (vi) dynamic update evaluation, and (vii) extension to other AI platforms.

[1]LLM supply chain graph: https://github.com/huggingface00/HuggingGraph

Table 1: The APIs used to extract data from Hugging Face.

API Name	Description
Model hub	Access the model hub to list, search, and download models and metadata.
Dataset	Access the datasets for discovery, metadata retrieval, and downloading.
Metrics	Access metrics for model evaluation, e.g., metric discovery, metadata retrieval, and calculation.
Search	Search name, tag, or other metadata for model and dataset.

2 Preliminary

The LLM supply chain encompasses the interconnected processes required for developing, deploying, and maintaining models [51]. This includes sourcing and preparing data to ensure high-quality and diverse datasets [51]. It also involves creating and training models [28]. Finally, it covers making trained models available through APIs [42]. In addition, LLMs can undergo adaptation, quantization, and fine-tuning, a process where they are tuned with domain-specific datasets to maximize performance on specific tasks [50], thus improving their accuracy and applicability.

This study mainly focuses on the relationships between models and datasets, which are the central parts of the whole LLM supply chain ecosystem. *We hope this study can not only provide insights on the LLM supply chain but also raise awareness and future research interests in this direction.*

3 Methodology

3.1 LLM Supply Chain Information Collection

To analyze the LLM supply chain ecosystem, we need a large dataset with such information. Fortunately, platforms like Hugging Face provide some APIs that allow us to access the model and dataset and collect their metadata information, which can be used to construct the supply chain ecosystem.

Table 1 summarizes the four types of APIs we used. In particular, (i) *the model hub APIs* allow access to the hub of existing models, including searching and downloading the model and its metadata. (ii) *The dataset APIs* allow access to the datasets for discovery, metadata retrieval, and downloading. (iii) *The metrics APIs* allow access to the metrics for model evaluation, including metric discovery, metadata retrieval, and calculation. (iv) One can use *the search APIs* to search the name, tag, or other metadata for models and datasets.

Handling missing information. Accurate construction of the LLM supply chain graph critically depends on the quality of metadata from the LLM platforms (e.g., Hugging Face), which might suffer from missing or incomplete data. To address this limitation, we apply the following two techniques, i.e., cross-reference links, and textual pattern extraction.

(i) Cross-reference links. The model or dataset description could miss the supply chain data fields for API queries, which could be embedded within statically or dynamically rendered HTML pages. In this example URL https://huggingface.co/models?other=base_model:finetune:meta-llama/Meta-Llama-3-8B, one can tell the

model "*Meta-Llama-3-8B*" is fine-tuned from the model in the previous webpage. To capture such information, we cross-reference the links of the filtered model listing webpages, extract model identifiers, enable the reconstruction of supply chain graph edges, and recursively trace model lineage from the leaf node. This scraping step complements API-based extraction and is only employed when reverse dependency data is otherwise inaccessible.

(ii) Textual pattern extraction. When structured metadata is absent, the model and dataset cards might mention dependencies in unstructured text descriptions. To capture that, we employ a named entity recognition (NER) method [29, 47] to extract the dependency relationships from the text. For example, the textual phrase like "fine-tuned from Llama-2" contains the *fine-tuned* keyword, which implies from which model this model is actually fine-tuned. Similarly, we also look into other words, such as, "train", and "adapt".

3.2 LLM Supply Chain Graph

With the collected metadata, we construct a directed heterogeneous graph to model the LLM supply chain. In this graph, a node denotes different types of datasets and models, including base, fine-tune, adapter, quantization, and merge models. An edge denotes the dependency relationship between them, including model-model, dataset-dataset, and model-dataset relationships.

Figure 2 shows a simplified supply chain subgraph centering on a base model *Meta-llama*. *(i) Model-model relationship.* To further identify the supply chain relationship, we will check the relevant data fields. In particular, given a model in Hugging Face, there are data fields "`finetune`" that show which models are fine-tuned from this model. Similarly, "*adapter*", "*quantization*", and "*merge*" show which models are adapted, quantized or merged from them, respectively. With such information, we can construct the supply chain relationship between the models. As shown in Figure 2, model *Llama-3.3-70B* is fine-tuned from the base model *Meta-llama*. Then, it is used by the models *Doctor-Shotgun* and *Llama-3.3-70B-4bit-Vision* to generate an adapter and quantization model, respectively.

(ii) Dataset–dataset relationship. The datasets within the LLM supply chain might overlap, build upon, or extend from each other. For example, a dataset may be a subset or modified version of another. To capture such information, we connect them with two types of edges. *(1) Subset relationships* arise when a dataset is explicitly documented as a subsample or partition of another. For instance, a dataset named "C4_200M" is described as a subset of "C4". *(2) Modified versions* represent updates or enhanced variants of existing datasets. For example, "TruthfulQA_v2" incorporates corrections and improvements over an earlier version, "TruthfulQA_v1".

(iii) Model-dataset relationship. To capture the model and dataset dependency, we use the metadata from both models and datasets. The metadata of a model might specify the datasets used for training or adapting. However, not all the models disclose such information. To capture more information, we find the metadata of a dataset contains a data field of "trained_fine_tune_models" on this dataset. Thanks to that, we are able to capture the accurate model and dataset relationships. In Figure 2, the datasets *The Pile* and *Chatgpt-prompt* have directed edges to model *Meta-Llama*, meaning that both datasets are used to train the model.

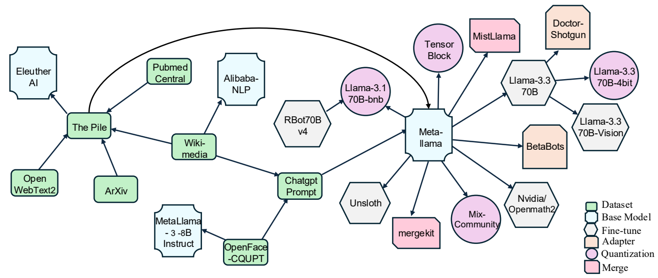


Figure 2: An example subgraph centering on base model "`Meta-llama`" from the complete LLM supply chain graph.

3.3 Supply Chain Graph Analysis

This supply chain graph can help to understand the transformational processes of the models and datasets. In particular, we can understand how base models evolve into their variants, including fine-tuned, adaptive, quantized, or merged models, and vice versa. Similar observations can be made for datasets. This would provide a clear view of how the base model (or dataset) is transformed for performing a particular task. In particular, we mainly perform two types of analysis, i.e., forward and backward analysis.

Forward analysis is the method of traversing the supply chain graph following the dependency edges of a chosen node in a forward-going way. This node (known as the root/source node) can be a dataset, a base model, a fine-tuned model, an adapter, or a quantized model. In particular, given a source node, we apply the graph traversal algorithm (e.g., breadth-first search (BFS) [45]) to traverse all the nodes (including both models and datasets) in a level-by-level pattern. To that end, this forward analysis will identify all the nodes that are reachable from the source node.

Model analysis example. In Figure 2, to analyze the forward supply chain of *Meta-Llama*, we trace its development from training datasets to subsequent adaptations. This model is fine-tuned into *Llama-3.3-70B*, enhancing its capabilities for specific tasks. Summarizing the forward supply chain of *Meta-Llama*, we identify the following four distinct forward supply chains: (i) Base model (*Meta-llama*) → fine-tuned model (*Llama-3.3-70B*) → another fine-tuned model (*Llama3.3-70B-Vision*). (ii) Base model (*Meta-llama*) → adapted model (*Doctor-Shotgun*). (iii) Base model (*Meta-llama*) → fine-tuned model (*Llama-3.3-70B*) → quantization model (*Llama-3.3-70B-4bit*). (iv) Base model (*Meta-llama*)) → merged model (*MistLlama*). These pathways illustrate the evolution trajectory of the base model *Meta-Llama* showcasing its progressive specialization and adaptation for various tasks.

Dataset analysis example. For the dataset, our supply chain analysis shows how different datasets connect and form a new dataset. This combination creates flexible resources that show how models perform in various areas. In Figure 2, the dataset *The Pile* is composed of multiple subsets, including *Wikimedia*, *Arxiv*, *Openwebtext2*, and *Pubmed Central*. Together, these datasets form a unified corpus that serves as training data for models like *Meta-LlaMA*.

Backward analysis, on the other hand, is the method of traversing the supply chain graph following the edges in a backward way. We accomplish this by traversing the directed graph also with BFS [26] in reverse, starting from the selected node and following the incoming edges. To that end, this backward analysis will identify all the nodes that can reach the source node.

Model and dataset analysis example. In Figure 2, analyzing the backward supply chain of model *RBot70Bv4*, we trace its lineage through its development stages. This model is fine-tuned from *Unsloth*, which in turn originates from its base model, *Meta-Llama*, and the datasets used to train the base model are *The Pile* and *Chatgpt-prompts*. Through this analysis, we establish the backward path, starting from the target model, i.e., *RBot70Bv4*, and tracing to its base model, *Meta-Llama*, revealing dependencies and transformations involved in its development. Similarly, we can analyze datasets.

3.4 Accommodating Dynamic Update

The hosted models and datasets on AI platforms are growing fast as new models are being developed every day. For example, between June 25 and July 15, 2025, we observed 80,703 new models (approximately 3,843 per day), 27,405 new datasets (approximately 1,305 per day) on Hugging Face only, which is just one of the many AI platforms. Therefore, we need to accommodate the dynamic update to accurately manage and analyze the AI supply chain.

Particularly, HuggingGraph accommodates the dynamic update in three steps. *(i) Scoping updated models or datasets.* At a time t, we keep a copy of the hosted models and datasets with their IDs. When we evolved to $t+1$, we get another copy of the hosted models and datasets with their IDs. The difference between them shows the updated models and datasets, including newly added or deleted. In our current implementation, we are keeping the update on a daily basis. *(ii) Metadata collection for the updated models or datasets.* For the identified updated models or datasets, we will collect their metadata using the same strategy as discussed in Section 3.1. To this end, we get the updated dependencies between models and datasets. That is, for the update at time $t+1$ compared to t, it can be represented as Δ_{t+1}. *(iii) Δ-based dynamic graph update.* Given the newly updated dependency Δ_{t+1}, and let G_t, G_{t+1} denote the graph at time t, $t+1$, respectively, then $G_{t+1} = G_t \cup \Delta_{t+1}$.

4 Experiments and Finding

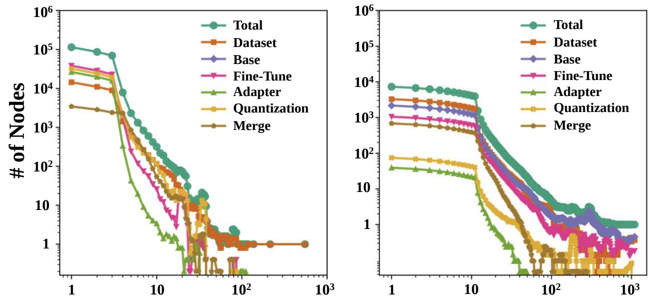
To deeply understand the relationships between models and datasets, we study seven critical research questions (RQs), which can offer valuable insights into the supply chain of the LLM ecosystem and potentially pave the way for future LLM development.

- **RQ #1**: What are the properties of LLM supply chain graph?
- **RQ #2**: What structural patterns emerge?
- **RQ #3**: What are the supply chain between LLM models?
- **RQ #4**: What are the supply chain between datasets?
- **RQ #5**: What are the relationships between models and datasets?
- **RQ #6**: What insights can be gained from the dynamic updates?
- **RQ #7**: How can HuggingGraph be applied to other platforms?

4.1 RQ #1: Supply Chain Graph Properties

This research question aims to understand the critical properties of LLM supply chain graph, i.e., graph basics and degree distribution.

Graph basics. The collected supply chain graph is a medium-scale directed heterogeneous graph with **402,654 nodes** and **462,524 edges** as of *June 30th, 2025*. In particular, there are six different types of nodes, including 28,384 base models, 115,211 fine-tuned, 79,254 adapters, 98,143 quantization models, 13,028 merges, and 68,634 datasets. The average degree is about 1.15, denoting that it is a very sparse graph. Furthermore, we identified substantial metadata missing. As of June 30, 2025, among 1.8 million models, only 50,156 (2.76%) include a model tree, while ~ 550K models lack any metadata beyond their name, with nearly 400K entries empty or invalid. Similarly, of the 450K datasets, only 68,634 (15.26%) provide datacards, leaving ~ 380K datasets without any usable metadata.



(a) # of In-degrees (b) # of Out-degrees

Figure 3: (a) Indegree distribution and (b) Outdegree distribution. X-axis represents degrees, and the Y-axis represents the number of vertices in a logarithmic scale.

This highlights a broader issue in the AI community, where a significant number of models and datasets lack consistent and structured documentation on the supply chain. This reflects the need of more transparent disclosure.

Degree distribution of a graph describes how node degrees (the number of edges connected to a node) are distributed across the graph. Figure 3 illustrates the indegree and outdegree distribution of the graph. We show not only the total distribution but also the distribution of six types of nodes, including base models, fine-tuned models, adapter models, quantization models, merged models, and datasets. We made two interesting observations. (i) This degree distribution in our supply chain graph shows a heavy-tailed behavior. In particular, the indegree distribution shows a large spread across different categories. The outdegree distribution follows a similar pattern but may differ in specific cases (e.g., adapters seem to have a more restricted degree distribution). The **heavy-tailed behavior** suggests that most nodes have low degrees, while a few central nodes (hubs) dominate the graph. In particular, the dataset *macrocosmos/images* has the highest indegree value of 550, and *Mistral-7B-v0.1* from "mistral AI" has the highest outdegree value of 1,093. Specifically, the base models act as high-degree hub nodes as they are heavily used by other task-specific models.

Finding #1: *The LLM supply chain graph is medium-scale, sparse, and heavy-tailed distribution. However, a significant number of models and datasets lack metadata, highlighting the need for more transparent supply chain documentation.*

4.2 RQ #2: Supply Chain Structural Analysis

This research question aims to understand the topology and evolution of the LLM supply chain. To achieve that, we analyze the structural properties with connectivity and community analysis.

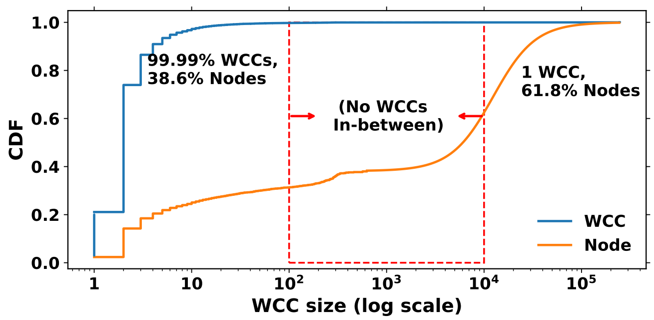


Figure 4: Cumulative distribution function (CDF) of WCC size.

Connectivity analysis analyzes the structural connectivity information. We performed weakly connected components (WCC), which identifies maximal sets of nodes that remain connected when edge directions are ignored. The total number of WCCs in our supply chain graph is 44,908. Figure 4 shows the cumulative distribution function (CDF) of the WCC distribution. We made two interesting observations. (i) The largest WCC covers 247,244 nodes, accounting for 61.8% of all the nodes. It reflects the dense interconnections that pervade the ecosystem. This vital element is essential for effective information sharing, resource allocation, and structural support and is the base of the ecosystem. In the largest WCC, major models are included, such as Gemma-2B, DistilBERT, and GPT-2. (ii) In contrast, the remaining WCCs collectively hold 38.6% of the nodes (i,e,.155,410 nodes), with most having 1, 2 or 3 nodes. This indicates a fragmented outer edge characterized by specialized models, rare datasets, or active experimental projects. The prevalence of these small, isolated pieces suggests niche attempts that lack integration with the overall system. For example, zhongqy/RMCBench (benchmarking dataset) and yigit69/bert-base-uncased-finetuned-rte-run_3 (recognizing textual entailment task) remain disconnected due to limited reuse or insufficient metadata.

We also computed strongly connected component (SCC), a maximal subgraph in which every node is reachable from every other via directed edges, identifying 398,198 SCCs. Remarkably, only 591 of these are non-trivial (size > 1), collectively encompassing 2,169 nodes (0.54% of the graph). The largest SCC comprises 478 dataset nodes, among them *tree-of-knowledge* and *OpenHermes-2.5*, forming a tightly-knit cluster. By contrast, the remaining 99.46% of nodes each reside in trivial (size-1) SCCs.

Community detection is the process of identifying groups or clusters of nodes within a graph that are more densely connected internally than with the rest of the graph. In the context of the LLM supply chain, it reveals semantically or functionally aligned subgraphs that reflect the patterns of reuse and task-specific models or datasets. We use the Louvain method [11], which is a greedy optimization method for maximizing modularity. Modularity is a measure of how well a graph is divided into communities, where a high modularity score indicates that most edges fall within communities rather than between them.

Table 2 summarizes the top-10 communities detected using the Louvain method. Our analysis reveals an exceptionally modular structure, with each of the top communities achieving a high modularity score of 0.96, indicative of strong intra-community connectivity. Collectively, these communities span a wide range of functional domains, underscoring the presence of well-defined, task-aligned clusters within the ecosystem. We made two interesting observations. (i) The largest community consists of 9,390 nodes and attains a modularity score of 0.96, indicating an extremely cohesive internal structure. It revolves around base models like OLMoE and CausalLM, and general-purpose datasets like prompt-perfect. This suggests a densely connected cluster facilitating widespread reuse and fine-tuning. (ii) Several other communities reflect clear task-based segmentation. For instance, Community 3 (7,388 nodes, modularity 0.96) focuses on benchmarking, with models like Wanxiang and datasets like marco-o1. Similarly, ID 5 (4,554 nodes, modularity 0.96) centers on instruction-tuning, connecting models like MedLlama-3-8B with curated datasets like dpo-mix.

Table 2: Top-10 Louvain communities sorted by size.

ID	Size	E.g. models	E.g. datasets	Modularity
1	9,390	OLMoE, CausalLM	prompt-perfect	0.96
2	7,388	qwen2.5_math	Marco-o1	0.96
3	6,989	Wanxiang	smartllama3.1	0.96
4	6,813	tinyllama	Llama-1B	0.96
5	5,163	Qwen2.5-32B	Matter-0.2	0.96
6	4,554	MedLlama-3-8B	dpo-mix	0.96
7	4,262	Electra, ArliAI	MixEval	0.96
8	3,947	aesqwen1.5b	llava	0.96
9	3,829	bert	TORGO	0.96
10	3,828	Mistral	vicuna_format	0.96

Finding #2: *The LLM supply chain graph features a dominant core (61.8% of nodes), while high modularity (0.96) reveals task-aligned, semantically coherent communities amid a fragmented periphery.*

4.3 RQ #3: Supply Chain Analysis of LLM Models

This research question aims to provide a holistic view of the dependencies between the models within the LLM supply chain, particularly from both base and task-specific models.

Base model impact. We would like to understand the impact of base models. Here, we quantify the impact of a base model as the number of task-specific models that depend on it. The more dependencies, the larger the impact it has. We start with a base model and perform forward analysis by computing a breadth-first search (BFS) following the outgoing edges to get that from our LLM supply chain graph. This leads to a forward subgraph, which denotes all the models that depend on the base model, including fine-tuned, adapted, quantized, or merged models.

Table 3 shows the top-10 base models sorted by the forward subgraph size, which is the number of impacted task-specific models. We make two interesting observations. (i) A base model can significantly impact the LLM supply chain ecosystem. For example, *Llama-3.1-8B* is a base model from Meta used for efficient text generation, code assistance, and research [19]. Due to its relatively small size, which allows for deployment in resource-constrained environments, making advanced AI accessible to broader stakeholders [15]. It has generated up to 7,544 models, including 1,710 fine-tuned versions, 1,542 adapters, 3,473 quantizations, and 1,693 merged models tailored to specific tasks. (ii) In terms of fine-tuning, the base model *Mistral-7B-v0.1* has been fine-tuned the most times, totaling 2,105. It is a faster and lighter version of the *Mistral* model from Mistral AI. It is obtained by training on a large corpus with grouped-query and sliding window attention by Mistral AI, delivering efficient text

Table 3: Top-10 base models sorted by forward subgraph size.

Base model	Total	Fine-tune	Adapter	Quanti-zation	Merge	Level
Llama-3.1-8B	7544	1710	1542	3473	1693	25
Mistral-7B-v0.1	6744	2105	2187	1435	1254	27
Qwen2.5-7B	6733	1972	1764	2516	1132	11
Meta-Llama-3-8B	5633	967	1511	2220	1967	21
Llama-3.1-70B	4063	698	281	2075	2519	11
Qwen2.5-32B	3909	1086	158	2311	1049	12
Qwen2.5-1.5B	3645	1300	1290	949	248	8
Qwen2.5-0.5B	3521	1669	1006	810	46	11
Qwen2.5-14B	3362	726	411	1880	1166	15
Meta-Llama-3-8B-Instruct	3118	640	405	1394	1305	34

Table 4: Top-10 models sorted by backward subgraph size.

Model	Model Type	Total	Fine-tune	Quanti-zation	Level	Base Model
command-r-1-layer	Finetune	40	39	0	39	c4ai
KoModernBERT	Finetune	21	20	0	20	ModernBERT
t5-small	Finetune	21	20	0	20	t5-small
clinical_260k	Finetune	20	19	0	19	clinical_180K
t5-small-finetuned	Finetune	17	16	0	16	t5-small
clinical_300k	Finetune	16	15	0	15	clinical_180K
clinical_259k	Finetune	16	15	0	15	clinical_180K
LeoPARD-0.8.1	Finetune	16	2	13	15	DeepSeek-R1
LeoPARD-0.8.2-4bit	Quantization	16	1	14	15	DeepSeek-R1
LeoPARD-0.8.1-4bit	Quantization	16	1	14	15	DeepSeek-R1

generation, NLP, and code assistance on consumer hardware for low-latency applications like chatbots and text classification [46].

Task-specific model analysis. Given a task-specific model, we want to understand how it evolves, meaning what other models it has relied on. To achieve that, for each task-specific model, we perform a backward analysis by running a BFS following the incoming edges. To that end, the derived subgraph shows the models it relies on. Table 4 shows the top 10 task-specific models sorted by the backward subgraph size, which is the number of models they rely on. We make two interesting observations. (i) A fine-tuned model, *command-r-1-layer*, illustrates the depth and complexity of transformations in the LLM supply chain. This model operates in bfloat16 (BF16) precision for efficient text generation and natural language understanding [37], originates from the base model *cc4ai*, and has undergone extensive lineage evolution before reaching its final form. Specifically, it depends on 40 upstream artifacts, including 39 other fine-tuned models, and spans 39 transformation levels in its backward lineage chain, as detailed in Table 4. (ii) We observed that adapters are mainly used for lightweight fine-tuning and merges for model integration, but task-specific models like *command-r-1-layer*, as optimized standalone derivatives, do not evolve from adapters or merges in their backward lineage [37].

Finding #3: *Base models like Llama-3.1-8B dominate the LLM supply chain, spawning thousands of derivatives, while task-specific models such as command-r-1-layer exhibit deep dependencies with other task-specific variants but avoid adapters or merges.*

4.4 RQ #4: Dataset Supply Chain Analysis

This research question aims to provide comprehensive insights into the different usages of the datasets within the LLM supply chain graph. There are two relationships between datasets. On one hand, one dataset can be created by combining a variety of other datasets from disparate sources. On the other hand, one dataset can serve as a building block for new datasets.

Table 5: Top-10 datasets by # of included & derived datasets.

Dataset	# of included	Dataset	# of derived
macrocosm-os/images	550	HuggingFaceH4	989
bespokelabs/Bespoke	215	CodeFeedback	857
databricks/databricks	139	MADLAD	850
Open-Orca/OpenOrca	121	Capybara	823
nguha/legalbench	117	Glot500	804
OpenAssistant/oasst1	112	dolphin-coder	756
LDJnr/Capybara	108	SlimOrca	726
kvn420/Tenro_V4.1	105	orca_dpo_pairs	687
teknium/OpenHermes	104	gutenberg	675
Anthropic/hh-rlhf	98	samantha	658

In the LLM supply chain graph, 68,634 datasets act as training datasets that are used for model training or generating new datasets. Table 5 presents the top 10 datasets ranked by the highest number of included and derived datasets. (i) We observe that a training dataset can include many small datasets. Sitting at the top is *macrocosm-os/images* [25] from macrocosm. It is included in 550 datasets and is a general-purpose image modification corpus used in advanced multimodal AI research and large-scale vision-language model training. Moreover, *bespokelabs/Bespoke* [13] from bespokelabs is part of 215 datasets, is a high-quality synthetic dataset designed to enhance multimodal AI research.

(ii) The other observation is that a single dataset can be derived to many datasets, showing the huge overlaps between the datasets and also the models trained with them. The right two columns of Table 5 show the top 10 datasets sorted by the maximum number of derived datasets they have been included in. The leading contributor, *HuggingFaceH4* from HuggingFace has been derived to 989 datasets. It is primarily used for natural language understanding and generation tasks, including chatbots, text generation, code completion, reasoning, and multilingual processing, enabling the training and enhancement of models specialized in advanced conversational and instruction-following capabilities [12]. Similarly, the *CodeFeedback* dataset from m-a-p has facilitated the creation of 857 datasets, which is a collection of high-quality code instruction queries designed to enhance the training of large language models (LLMs) for code generation, debugging, and explanation tasks, enabling improved performance in complex programming scenarios[32].

Finding #4: *Datasets play critical roles in training with 68,634 datasets contributing to model development through inclusion and derivation, as seen in macrocosm-os/images and HuggingFaceH4.*

4.5 RQ #5: Supply Chain between Models and Datasets

This research question aims to explore the interconnections between models and datasets within the supply chain graph. It provides valuable insights from dual perspectives, including one dataset versus multiple models and one model versus multiple datasets.

One dataset versus multiple models refers to the case when a single dataset is used to train multiple models. Table 6 shows the top 10 datasets based on the number of models trained on them. In particular, *Mistral-7B-v0.1* takes the leading position and is a widely adopted open-source dataset known for its strong performance in general-purpose language understanding and generation tasks. It has

Table 6: Top-10 datasets sorted by # of models trained.

Dataset	Total	Fine-tune	Adapter	Quantization	Merges
Mistral-7B-v0.1	1093	300	300	193	300
TinyLlama-1.1B-v1.0	728	300	300	100	28
open_llama_3b	304	15	285	4	0
Yarn-Mistral-7b-128k	301	8	279	14	0
WizardVicuna-open-llama	280	12	261	7	0
TinyLlama-1.1B-v0.6	266	10	243	13	0
Yarn-Mistral-7b-64k	248	0	242	6	0
Nous-Capybara-7B-V1	213	11	174	27	1
MAmmoTH2-7B	213	0	0	3	210
Starling-LM-7B-alpha	210	10	165	18	17

been used to train 1,093 models, including 300 fine-tuned variants, 300 adapters, 193 quantized models, and 300 merged models, highlighting its broad adoption across diverse model derivation strategies.

In addition, the dataset *TinyLlama-1.1B-v1.0*, a compact and efficient model variant designed for low-resource deployment, is used to train 728 models, featuring 300 fine-tuned variants and 300 adapters. Similarly, *open_llama_3b*, an open-access dataset of LLaMA, supports 285 adapter-based models, indicating a preference for lightweight, modular adaptation. The dataset *Yarn-Mistral-7b-128k* also shows significant reuse, contributing to 279 adapters and 14 quantized models. Furthermore, *MAmmoTH2-7B* stands out with 210 merged models, showcasing its role in ensemble-style model fusion rather than traditional fine-tuning or adapter strategies. Lastly, the dataset *Starling-LM-7B-alpha*, known for alignment-focused training, contributes to a diverse range of downstream models, including 165 adapters and 18 quantized versions, illustrating its utility in fine-tuning and compression workflows.

One model versus multiple datasets refers to the case when an LLM model is trained with multiple datasets. We observed that *DeBERTa-ST-AllLayers-v3.1*, a fine-tuned variant of the DeBERTa architecture, takes the top position, having been trained on 116 different datasets. Its adapter-based counterpart, *DeBERTa-ST-AllLayers-v3.1bis*, also leverages the same number of datasets via adapter-based training, emphasizing modular reuse across tasks.

In addition, models like *static-similarity-mrl-mul-v1* and *static-similarity-mrl-multilingual* are both fine-tuned on 108 datasets, indicating their role in multilingual and multi-task similarity-based retrieval applications. The *ModernBERT-base-embed* and *Llama-3.2-3B-Instruct* families show strong dataset diversity as well, with 88 and 87 datasets, respectively, across fine-tuning and quantized variants (e.g., GGUF format). Interestingly, most of these models are fine-tuned, specifically, 8 out of the top 10, highlighting a trend where base models are transformed into task-specific variants through diverse training datasets. This pattern suggests that fine-tuning remains a dominant strategy for adapting base models to downstream tasks across heterogeneous data sources.

Finding #5: *Models and datasets exhibit strong bidirectional interdependence, with datasets like Mistral-7B-v0.1 spawning hundreds of models, while models such as DeBERTa-ST-AllLayers-v3.1 leverage diverse datasets to enhance adaptability, highlighting the critical role of dataset-model interactions in advancing AI.*

4.6 RQ #6: Dynamic Update Evaluation

This research question aims to understand the dynamic update of the LLM supply chain. Following the method discussed in Section 3.4, we perform a daily-based data collection by capturing how many nodes and edges are added and deleted each day.

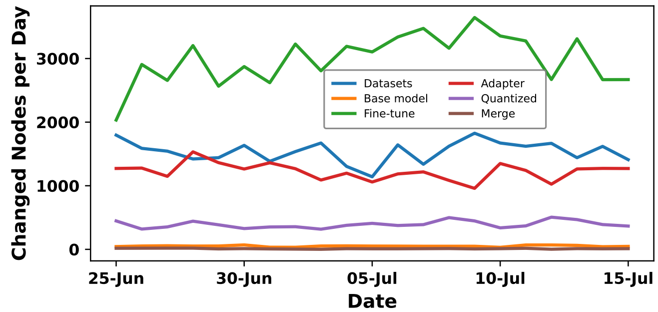


Figure 5: The number of changed models and datasets on Hugging Face from June 25 to July 15, 2025.

Figure 5 illustrates the sum of daily added and deleted of six key node categories (base, fine-tuned, adapters, quantized, merge variants, and datasets) from June 25 to July 15, 2025. We make three interesting observations. (i) The daily dynamic update is significant. That is, an average of 4,622 models are changing every day, including ~3,843 model additions and ~779 deletions. In addition, about 1,538 datasets are changing each day, containing ~1,305 dataset additions and ~233 deletions. An addition occurs when a new model or dataset is uploaded to the Hugging Face platform. This includes base models, task-specific variants, and new training datasets. A deletion refers to the removal of such nodes, often due to licensing issues, privacy concerns, or contributor decisions, such as replacing outdated models or withdrawing low-quality or sensitive datasets.

(ii) Fine-tuned models dominate daily activity, averaging over 2,988 changes per day, followed by consistent contributions from adapters (~1,224/day) and datasets (~1,539/day). Noticeable spikes, such as on July 7 and July 9, align with major events like the *Mistral-Fusion-v3* fine-tuning wave and dataset updates such as *HFTime2025-News*. (iii) Furthermore, adapter uploads peaked at 1,249 on June 28, while quantized variants reached 381 on July 9, driven by releases such as *QWin-GGUF-7B*. These patterns demonstrate HuggingGraph's ability to capture evolving supply chain dynamics at a fine-grained level.

Finding #6: *The LLM supply chain exhibits continuous and high-volume daily changes, driven by frequent additions and deletions of models and datasets. This reflects a rapidly evolving and highly dynamic ecosystem shaped by active contributor behavior.*

4.7 RQ #7: Generability to Other AI Platforms

To validate HuggingGraph's generalizability beyond Hugging Face, we applied our pipeline to another AI platform, Kaggle [6]. As of July 25, 2025, Kaggle hosts 470 base and task-specific models with 3,146 variants and approximately 502K datasets. Using Kaggle's kernel and dataset APIs, we collected 2,640 models and 105,867 datasets. This significant gap is due to lack of the models' and datasets' metadata. Of the datasets retrieved (~105K), only 137 datasets were included in our graph, as most lacked standardized documentation or traceable links to models. Many are standalone, poorly described, or lack contextual information, a challenge also observed on Hugging Face.

We follow the same way to construct a heterogeneous graph consisting of 2,777 nodes, which include 2,640 model nodes, comprising 59 base models, 2,410 fine-tuned, 171 quantization models, and 137 datasets. The graph contains a total of 3,990 edges, on which we observed seven types of edges, (i) base model → fine-tuned model (467 edges), (i) base model → quantization model (62 edges), (iii) fine-tuned model → fine-tuned model (1,696 edges), (iv) fine-tuned model → quantized model (107 edges), (v) quantized model → quantized model (1 edges), (vi) dataset → fine-tuned model (1,614 edges), and (vii) dataset → quantization model (43 edges).

We observed that the average degree is 1.44, indicating that the graph is sparse. We made two interesting observations. (i) The degree distribution is heavy-tailed and skewed: out of 2,777 total nodes, 2,305 nodes (≈83%) have a total degree of 1. Most nodes have low degrees, while a few highly connected hubs dominate the graph. For example, in-degrees range from 0 to 4 (with *NaN* peaking at 4), and *tensorflow/mobilenet-v1* has the highest out-degree of 64, followed by *google/nnlm* with 56. (ii) Furthermore, the graph contains 448 weakly connected components (WCCs), reflecting high fragmentation. However, the largest WCC includes 65 nodes, suggesting the presence of a moderately sized core subgraph.

Finding #7: *The resulting graph exhibits structural properties consistent with our Hugging Face analysis, including a heavy-tailed degree distribution, sparse connectivity, and strong modular fragmentation, demonstrating the robustness and generalizability of our pipeline across platforms despite metadata limitations.*

5 Use Case

HuggingGraph presents a technique to analyze the supply chain of the LLM ecosystem. The proposed graph can be used for various applications, e.g., auditing provenance, identifying biases, and revealing trends like quantized model scarcity, aiding researchers and platform maintainers. We discuss the following two use cases.

Use case #1: Tracing lineage and dependencies in the LLM supply chain. In the LLM ecosystem, models are frequently built upon others through fine-tuning, adapter training, or quantization, forming complex chains of dependencies. However, when these relationships are not explicitly visible, it becomes difficult to verify where a model comes from, whether it inherits bias from upstream datasets, or if it complies with licensing constraints. HuggingGraph can be used to address this challenge by constructing the supply chain of models and datasets, uncovering both direct and derived dependencies, even when they are not formally documented. For example, it can trace how the model Meta-llama indirectly relies on a dataset like Wikimedia via Chatgpt-prompt (Figure 2). This transparency supports developers, auditors, and policymakers in validating provenance, detecting risks, and enabling trustworthy AI.

Use case #2: Identifying critical nodes and structural vulnerabilities. In the LLM ecosystem, certain models (e.g., gemma-2b) and datasets (e.g., The Pile) are reused so frequently that they become critical structural hubs, where failure or removal of them could disrupt numerous downstream dependencies. These hidden single points of failure are difficult to detect without a comprehensive view of resource interconnections. HuggingGraph can be used to address this by modeling the supply chain as a graph and analyzing node connectivity to surface highly reused models and datasets with significant inbound or outbound links. This visibility enables maintainers to safeguard vital assets and helps developers mitigate the risk of overreliance on fragile or under-maintained components.

6 Related Work

This section aims to provide in-depth coverage of the current research landscape concerning the opportunities within the LLM supply chain, mainly emphasizing the different dimensions of the relationship between the models and datasets, focusing on the model and dataset hosting platforms [16, 41].

LLM supply chain perspectives in AI. LLMs mark the revolutionary era in AI, with the edge passing through an exponential growth phase. A recent paper presents LLMs key components, including model infrastructure, lifecycle, and downstream applications [51]. Another work showed that reusing these models has become widespread, which encourages the sharing and adaptation of base models on a larger scale [22]. An open-source AI ecosystem, such as Hugging Face, hosts a broad range of LLMs and datasets and, therefore, plays an important role in democratizing AI technologies [38]. The base models are key ingredients in such an ecosystem [52]. They capture vast amounts of information from various datasets, allowing for effective task-specific variants like fine-tuning [18]. This trend underscores the significant impact of technological advancements on AI democratization and innovation [10].

Relationship analysis between LLM models and datasets. A recent study investigates the practical adaptation of base models to specific areas and tasks. Multitask fine-tuning has demonstrated the potential to enhance performance on target tasks with scarce labels [53]. In plant phenotyping, adapting vision-based models by techniques like adapter tuning and decoder tuning has shown results comparable to those of leading task-specific models [8]. The Quadapter technique for language models tackles quantization difficulties by incorporating learnable parameters that scale activations channel-wise, mitigating overfitting during quantization-aware training [36]. These findings underscore the efficacy of various adaptation approaches in improving base model performance across areas.

From the above, we can see that models heavily depend on each other for fine-tuning, adaptation, quantization or merger. Building on these insights, two other works have indicated that serious security vulnerabilities may encumber the LLM supply chain to a few developers [23, 35]. These factors may affect the diversity of innovation. The authors relate several challenges arising during the software engineering, security, and privacy of different relations and components involved in model creation and deployment [21, 51]. Moreover, the vulnerabilities can be transferable from one model to another model during the fine-tuning process [17].

7 Conclusion

This project studies the relationships between models and datasets in the LLM ecosystem, which are the central parts of the *LLM supply chain*. First, we design a methodology to systematically collect the supply chain information of LLMs. With that, we construct a large directed heterogeneous graph, having *402,654 nodes* and *453,469 edges*. Then, we perform different types of analysis and make multiple interesting findings.

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