

Models All the Way Down

Auditing the **Invisible Dependencies** of Modern LLMs



Sanjay Adhikesaven*, Haoxiang Sun*, Sewon Min



LLMs start helping build other LLMs

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Olmo 3 Base

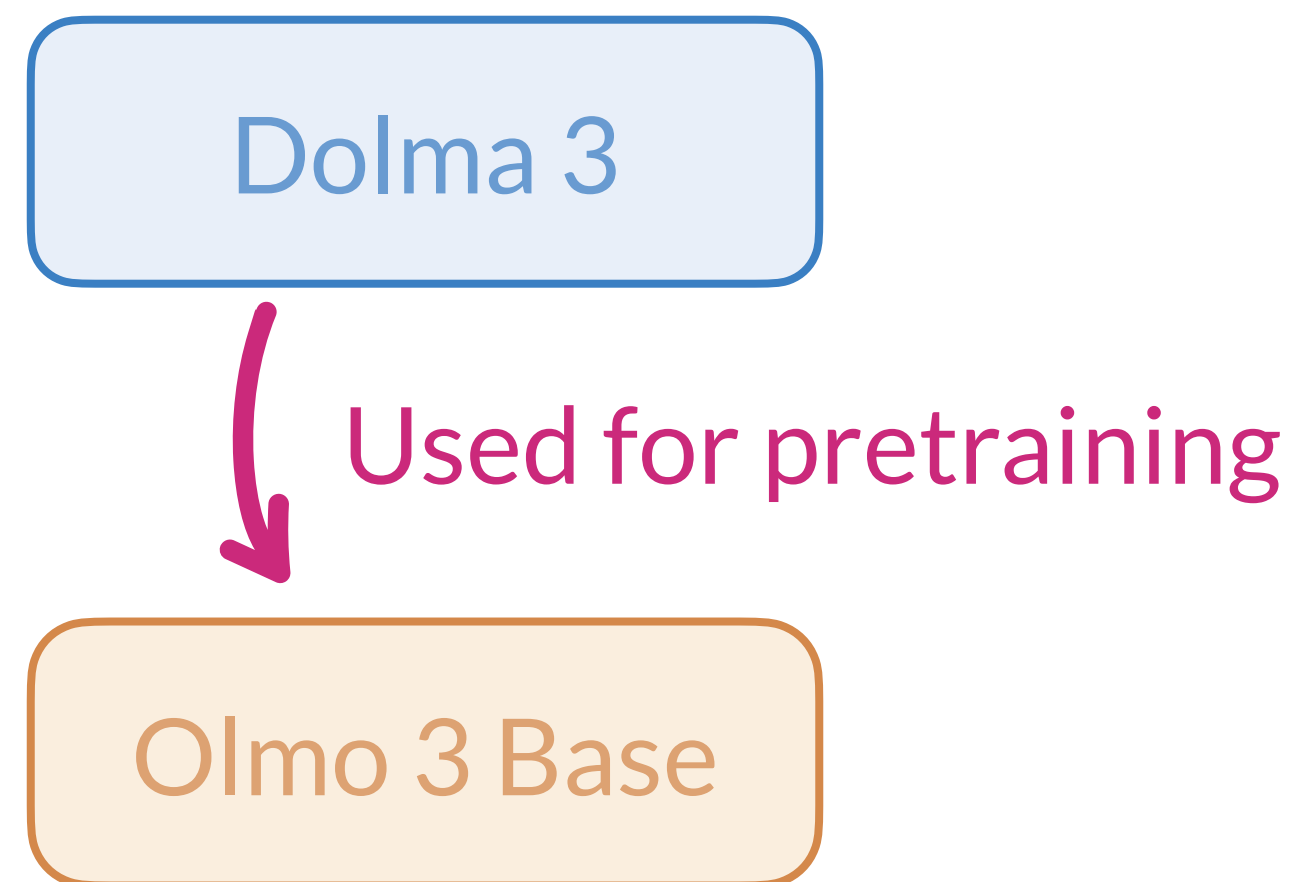
LLMs start helping build other LLMs

Used for pretraining

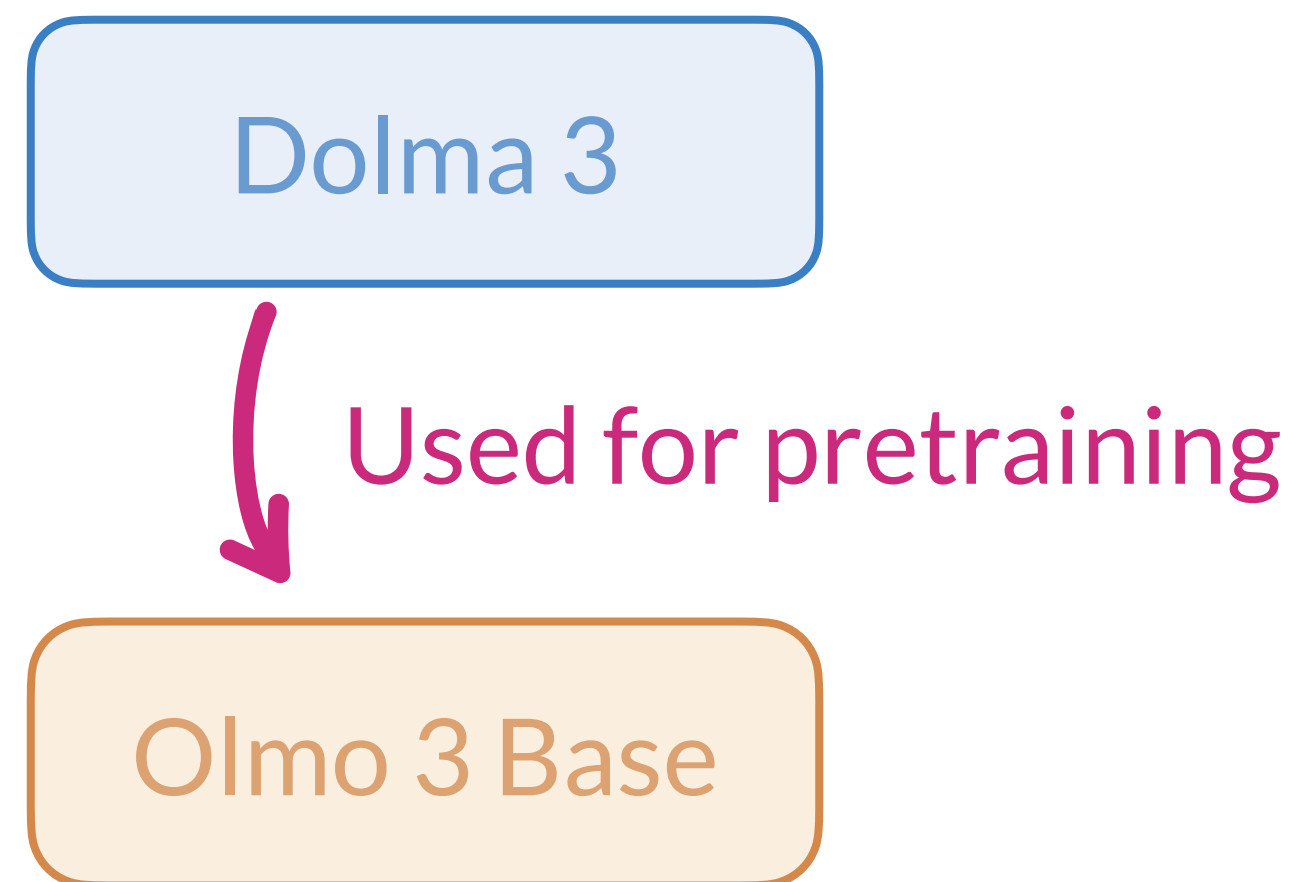


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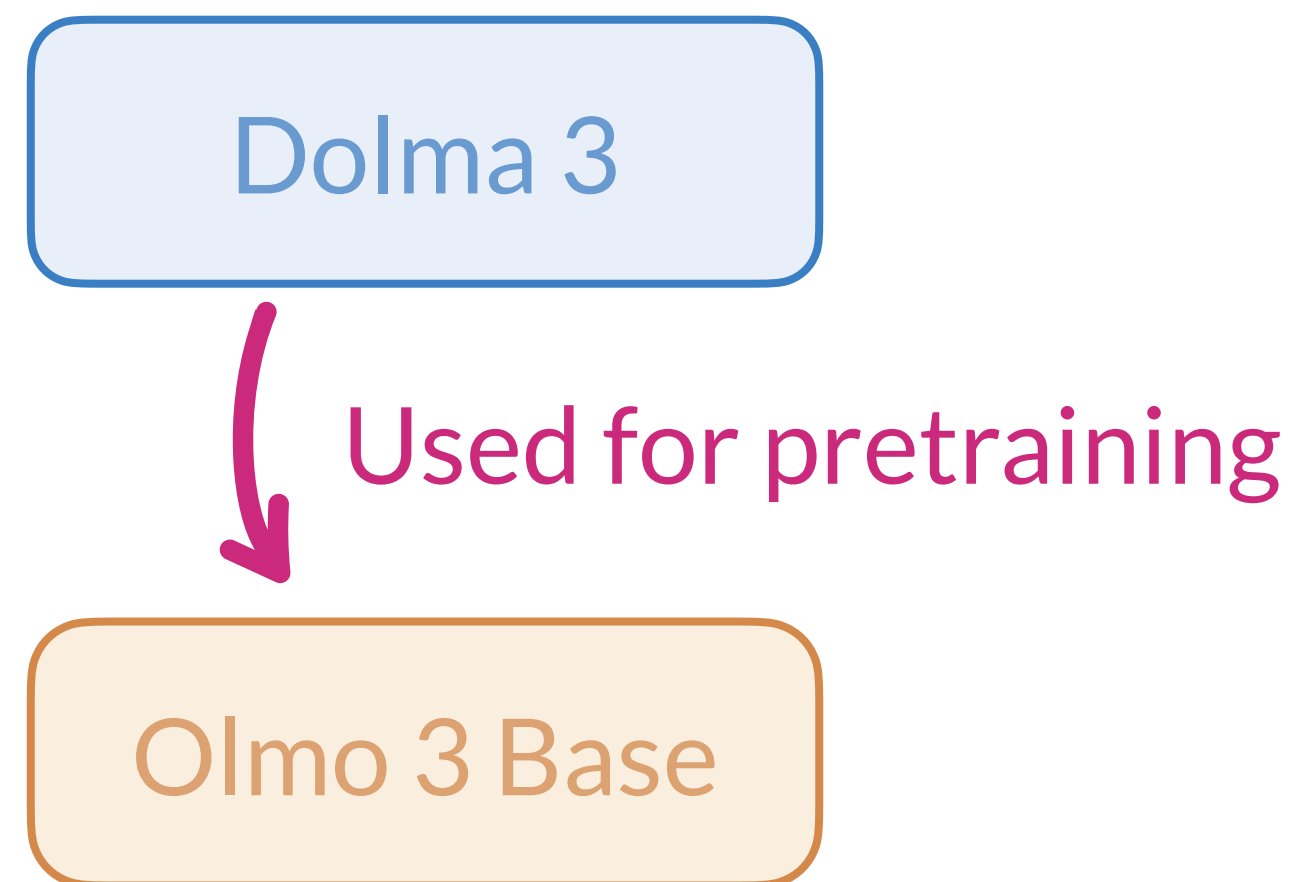


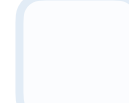
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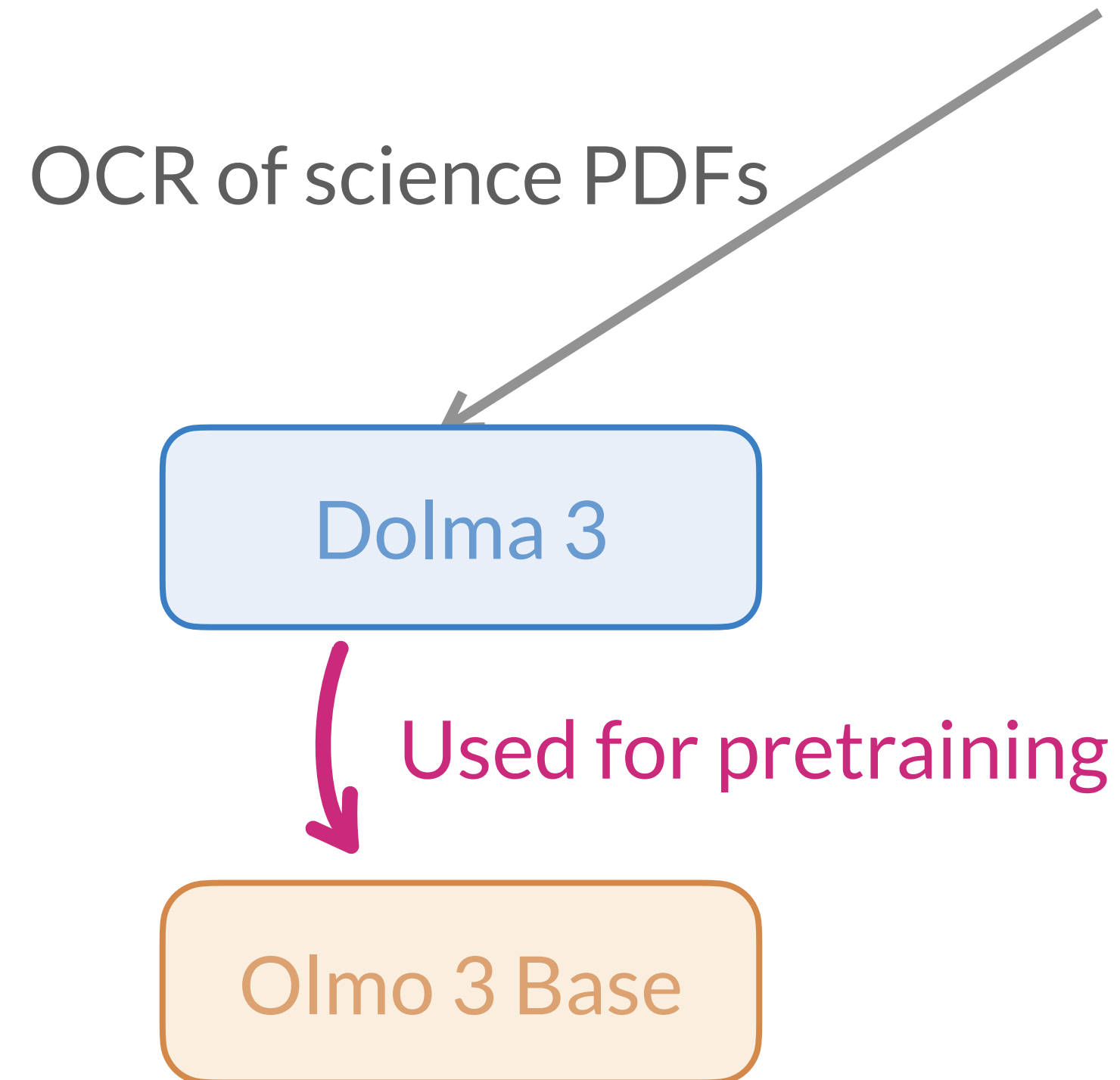
 Models  Datasets

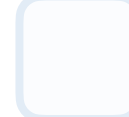
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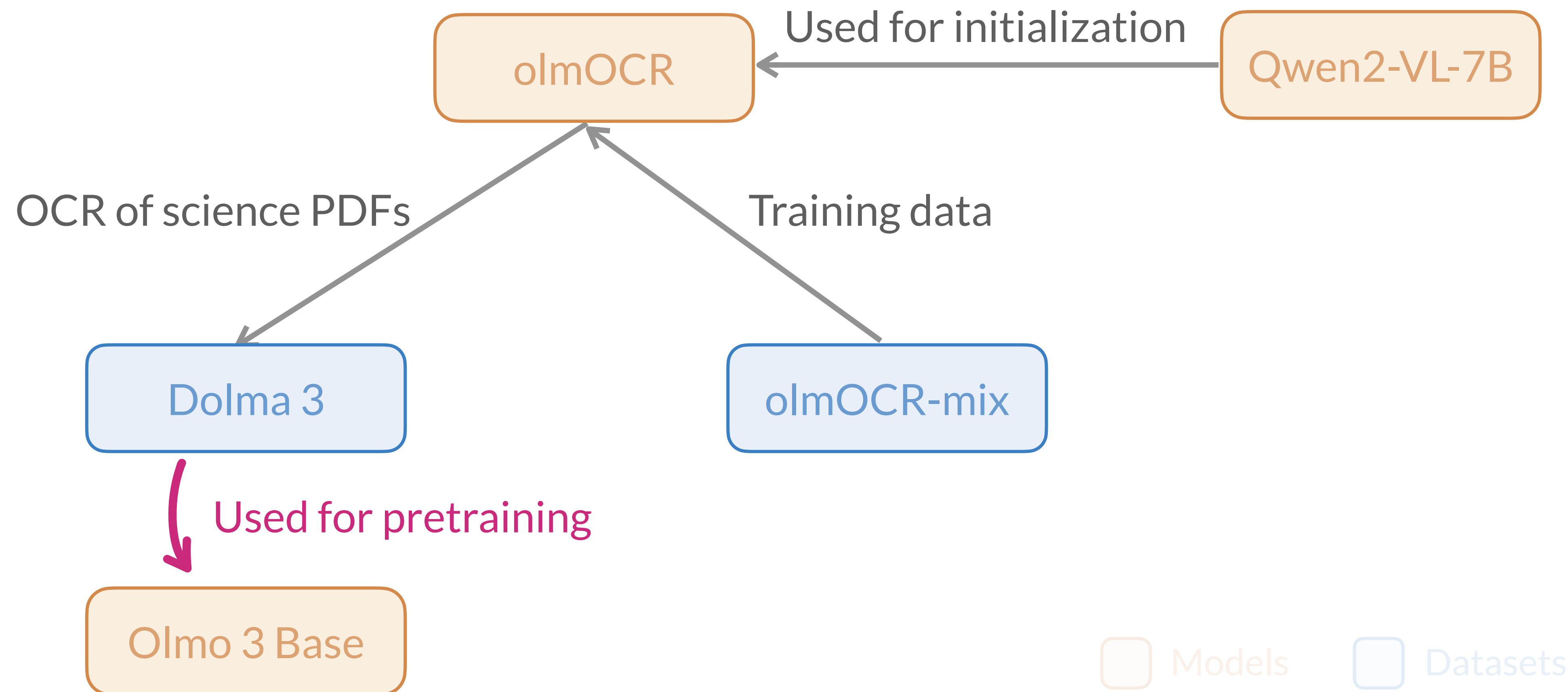


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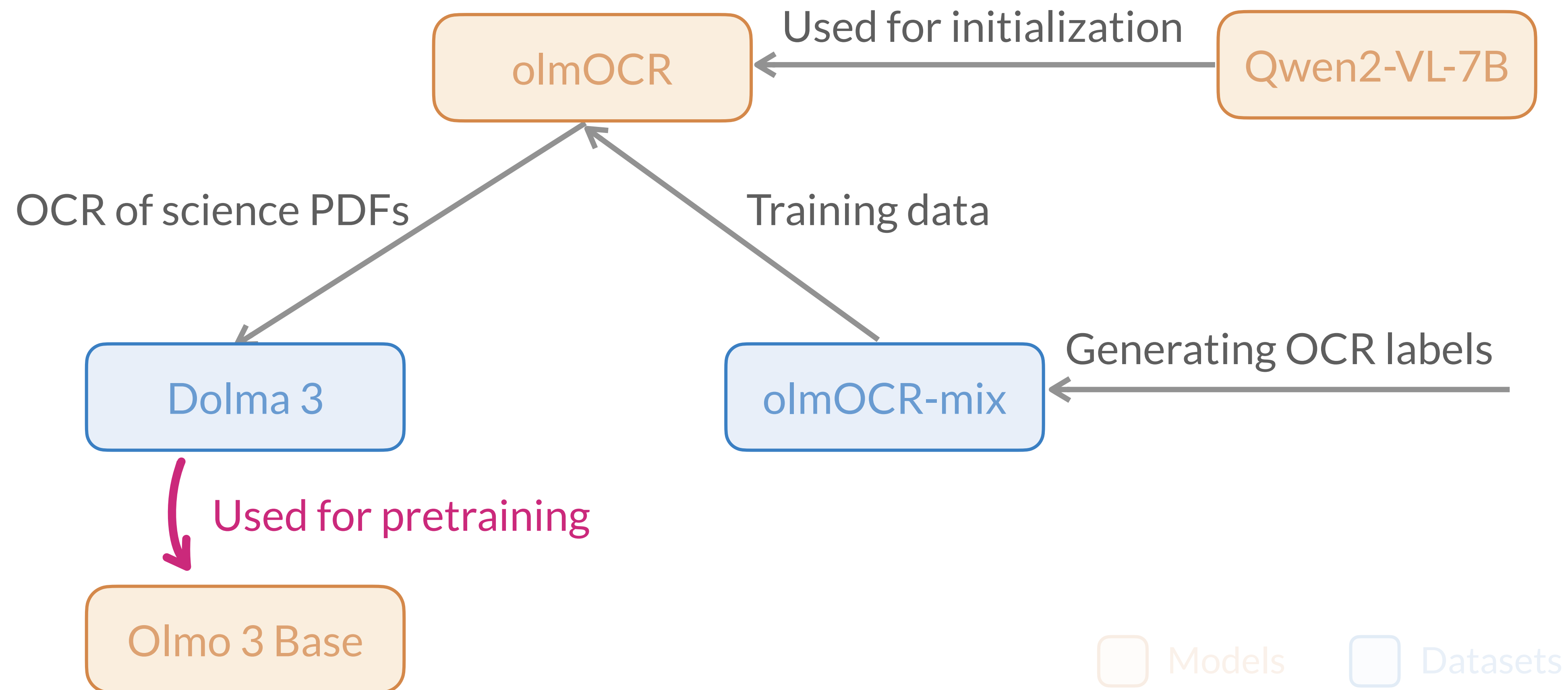
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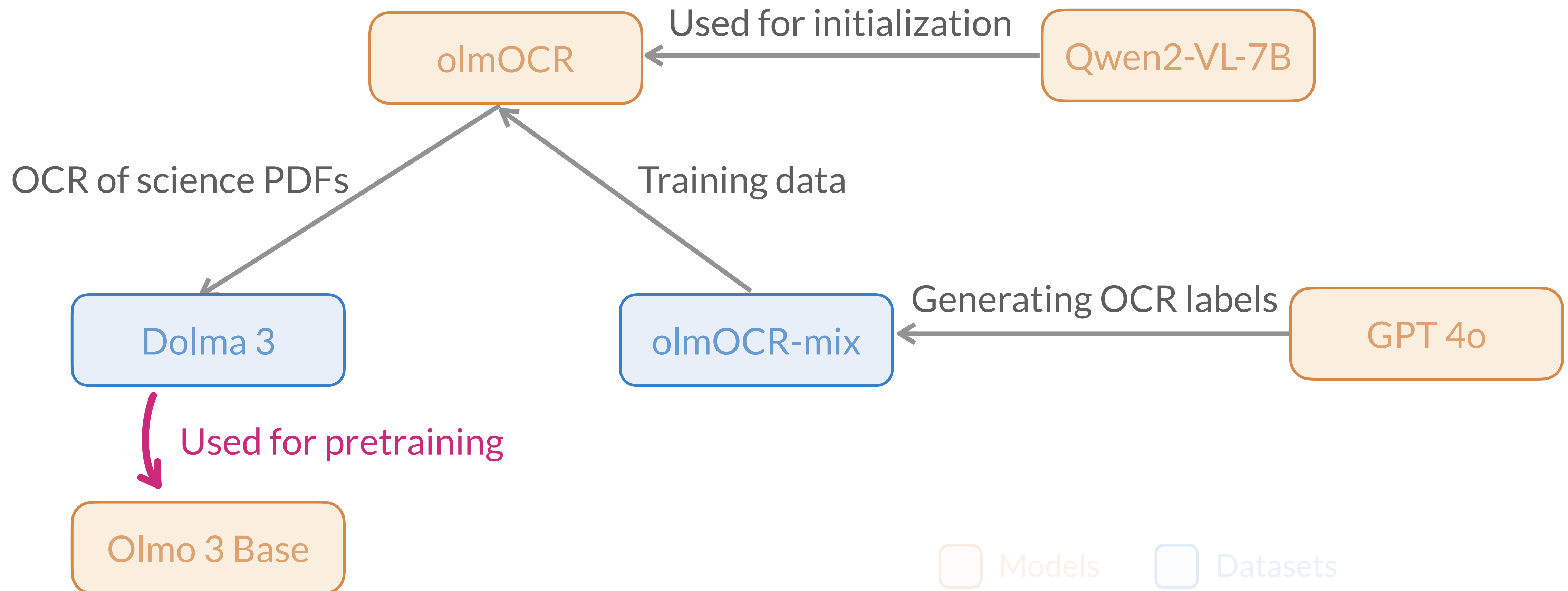
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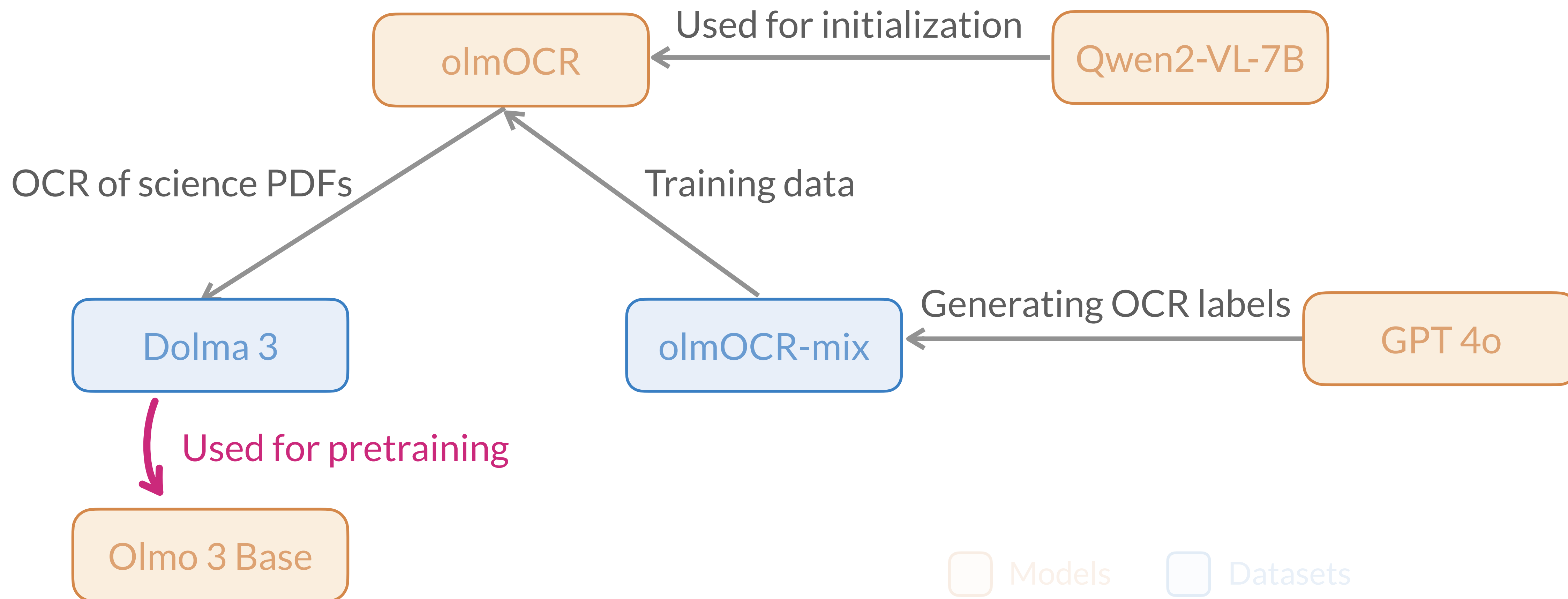
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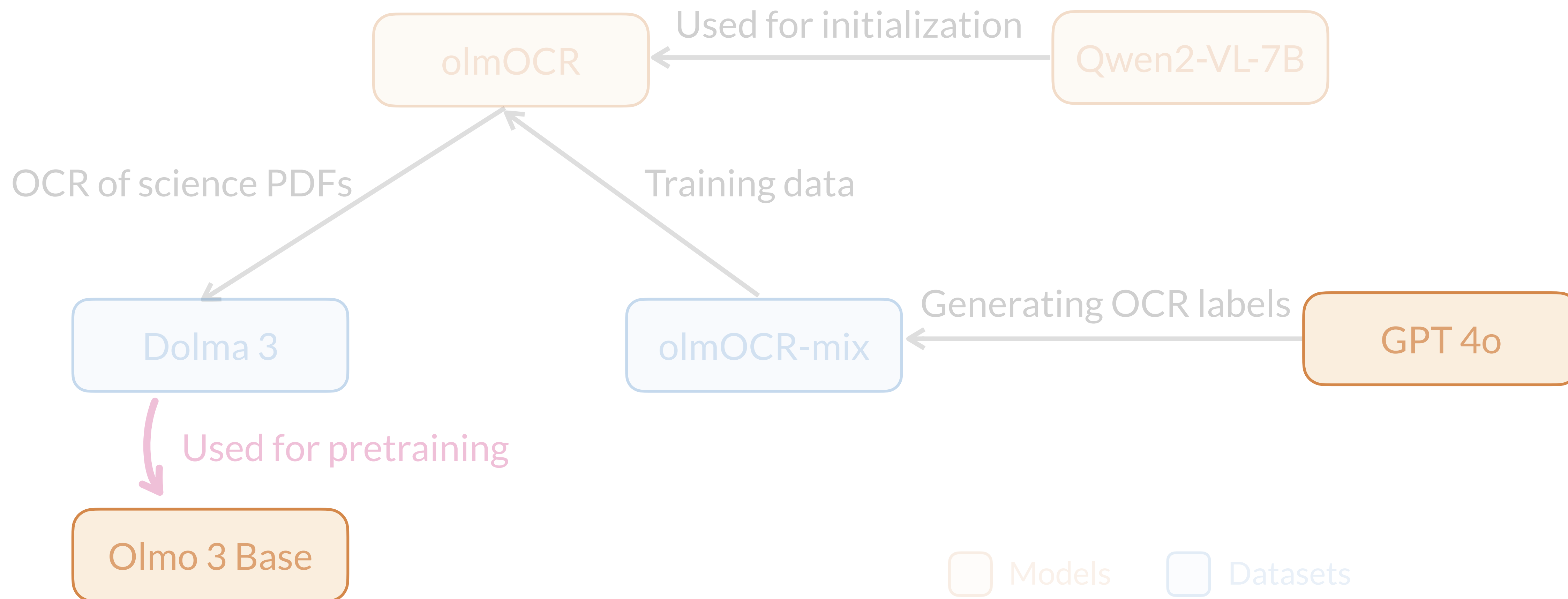
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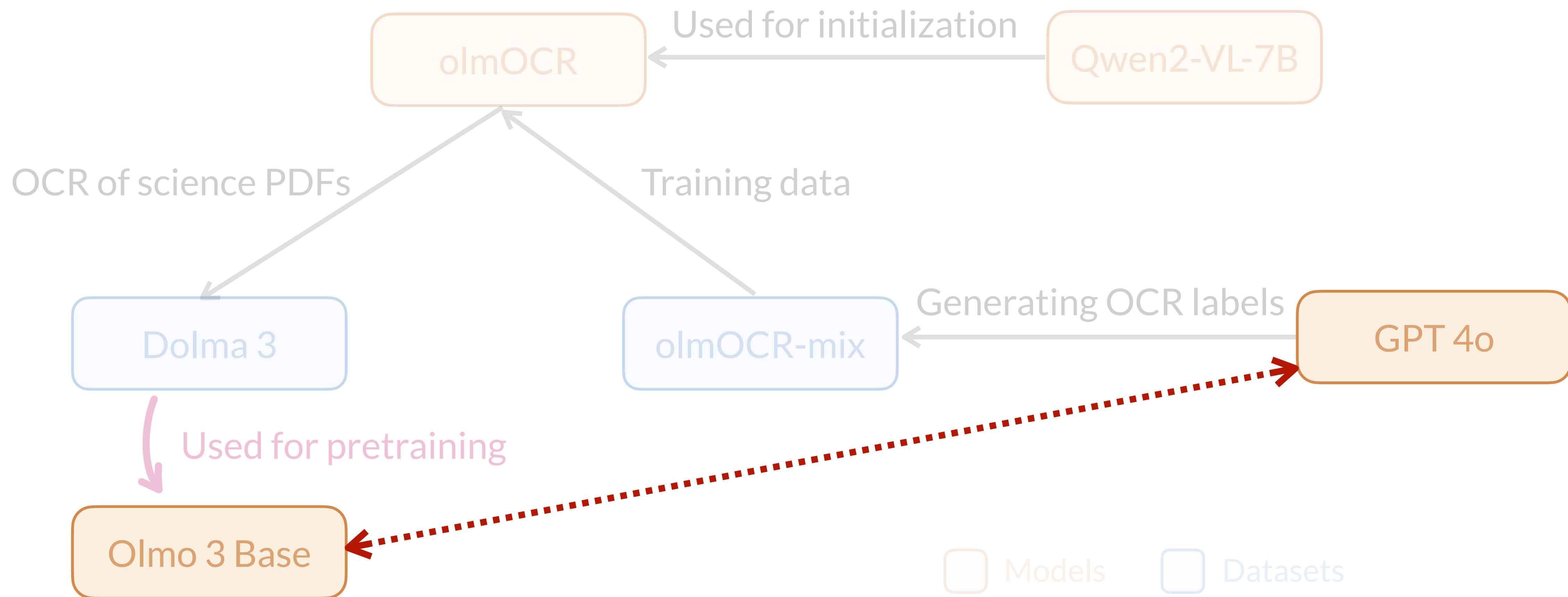
Complex dependencies of LLM development



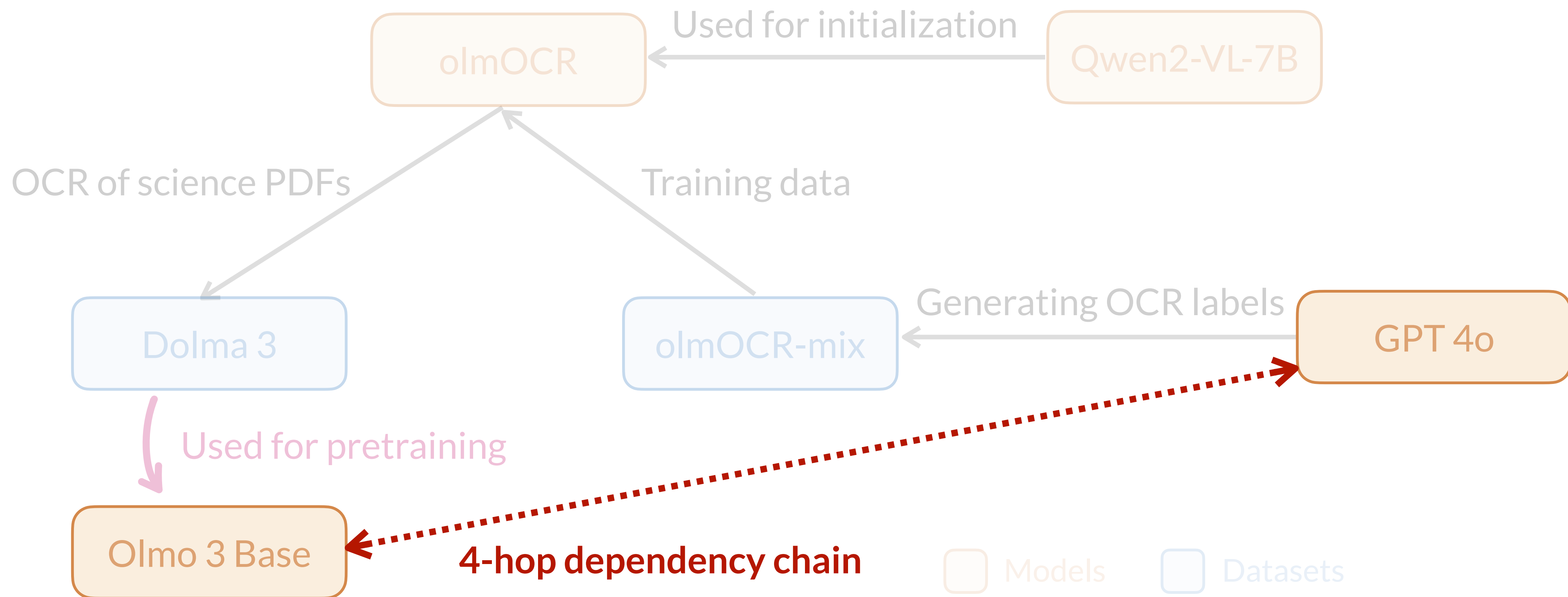
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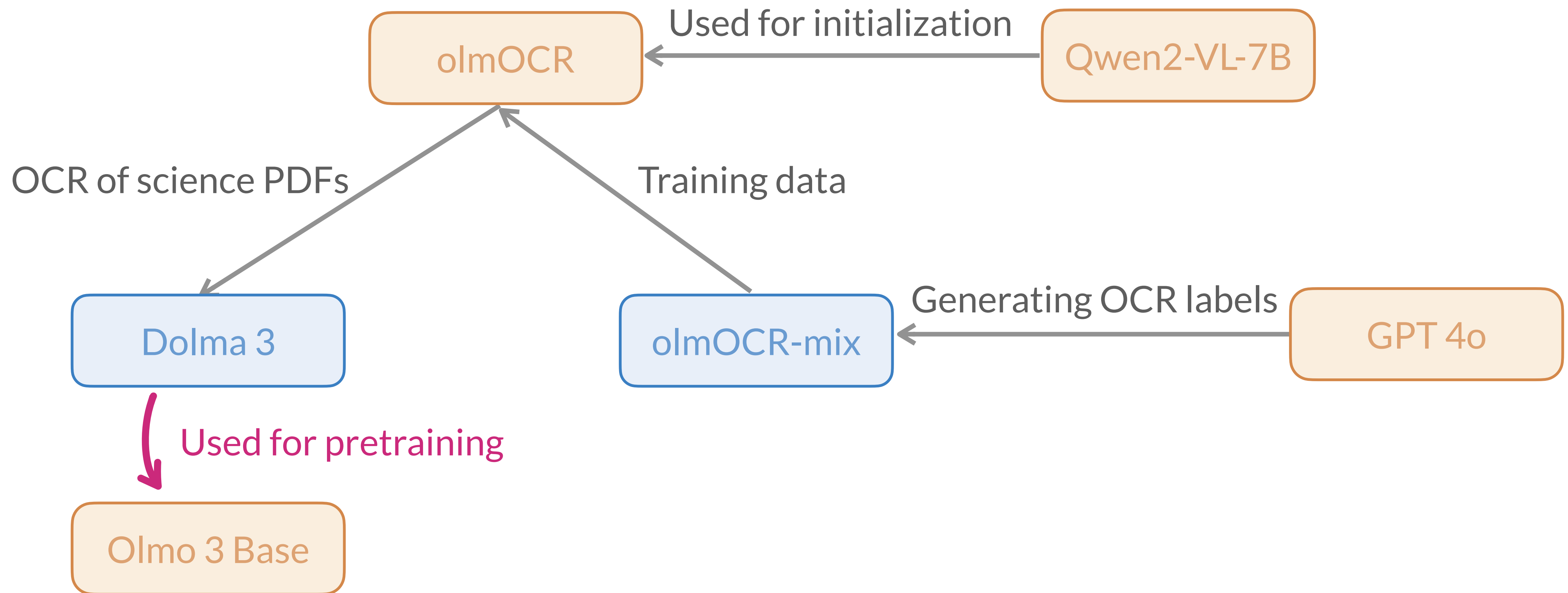
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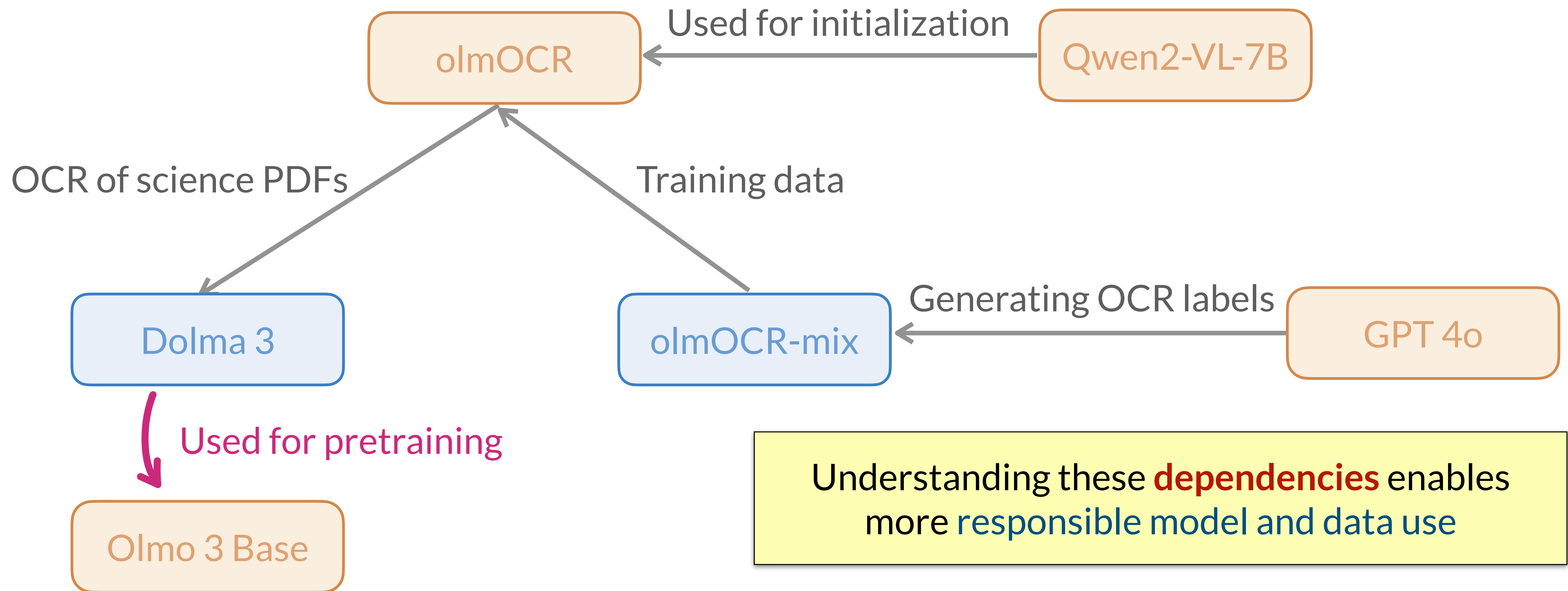
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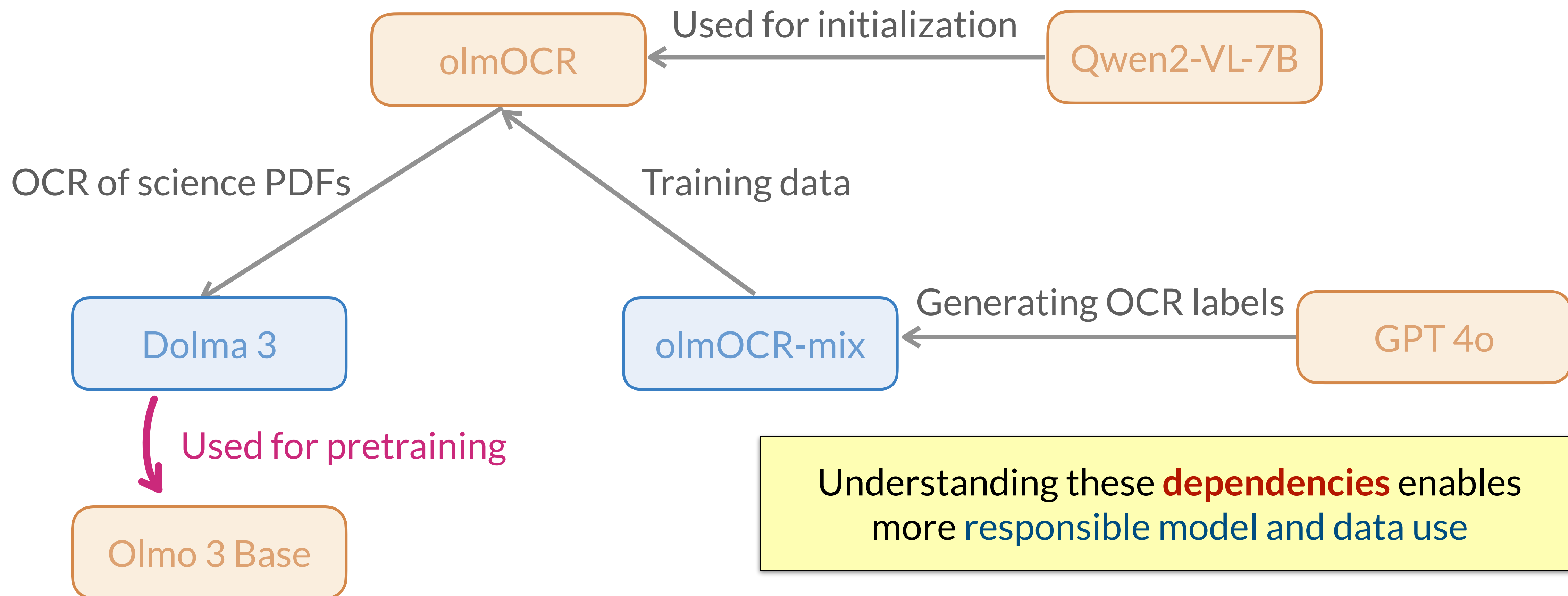
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Complex **dependencies** of LLM development



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We will show later what will happen if we do not care about dependencies - license obligations, data contamination, etc.

Complex dependencies of LLM development

olmOCR

Dolma 3

Olmo 3 Base

Complex dependencies of LLM development

olmOCR

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Olmo 3 technical report

The Olmo 3 family is the strongest collection of fully-open base models, outperforming Stanford Marin (Hall et al., 2025), Apertus (Apertus Team, 2025), and LLM360 K2-V2 (Team et al., 2025). To achieve these results, we construct new datasets for every stage of the model flow. This includes **DOLMA 3**, our pretraining data mix encompassing carefully-sampled natural data from crawled sources, our midtraining mix of high-quality data designed to jump-start reasoning, and a large collection of science-focused PDF documents that unlock

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Dolma 3 dataset card

olmOCR

Datasets:  allenai/**dolma3_mix-6T-1025-7B** 

Source	Doc Type	Tokens	Bytes (uncompressed)	Documents	License
common_crawl	web pages	4.51T	18.0TB	3.15B	ODC-BY
olmocr_science_pdfs	academic papers	805B	3.22TB	83.8M	ODC-BY

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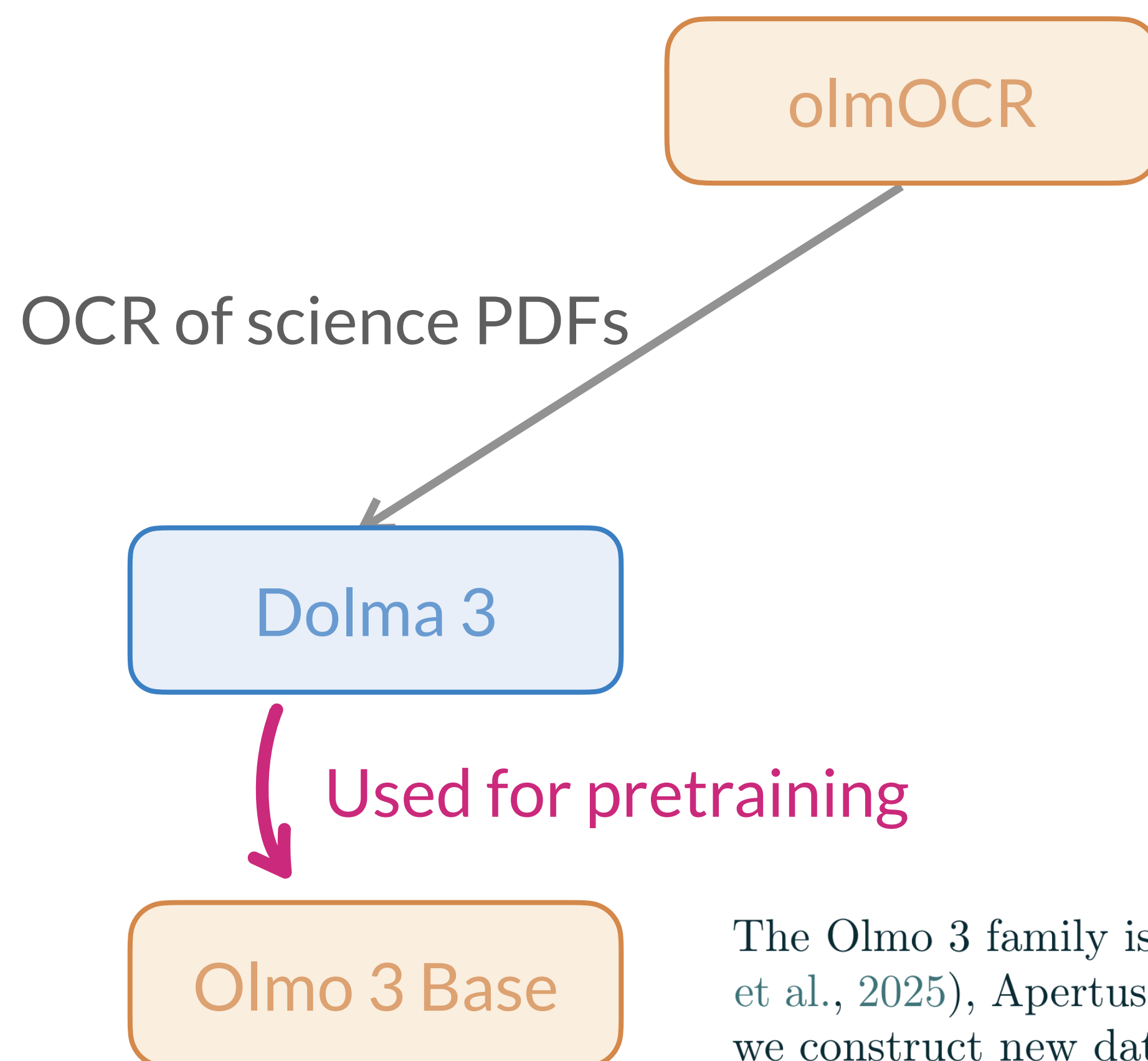
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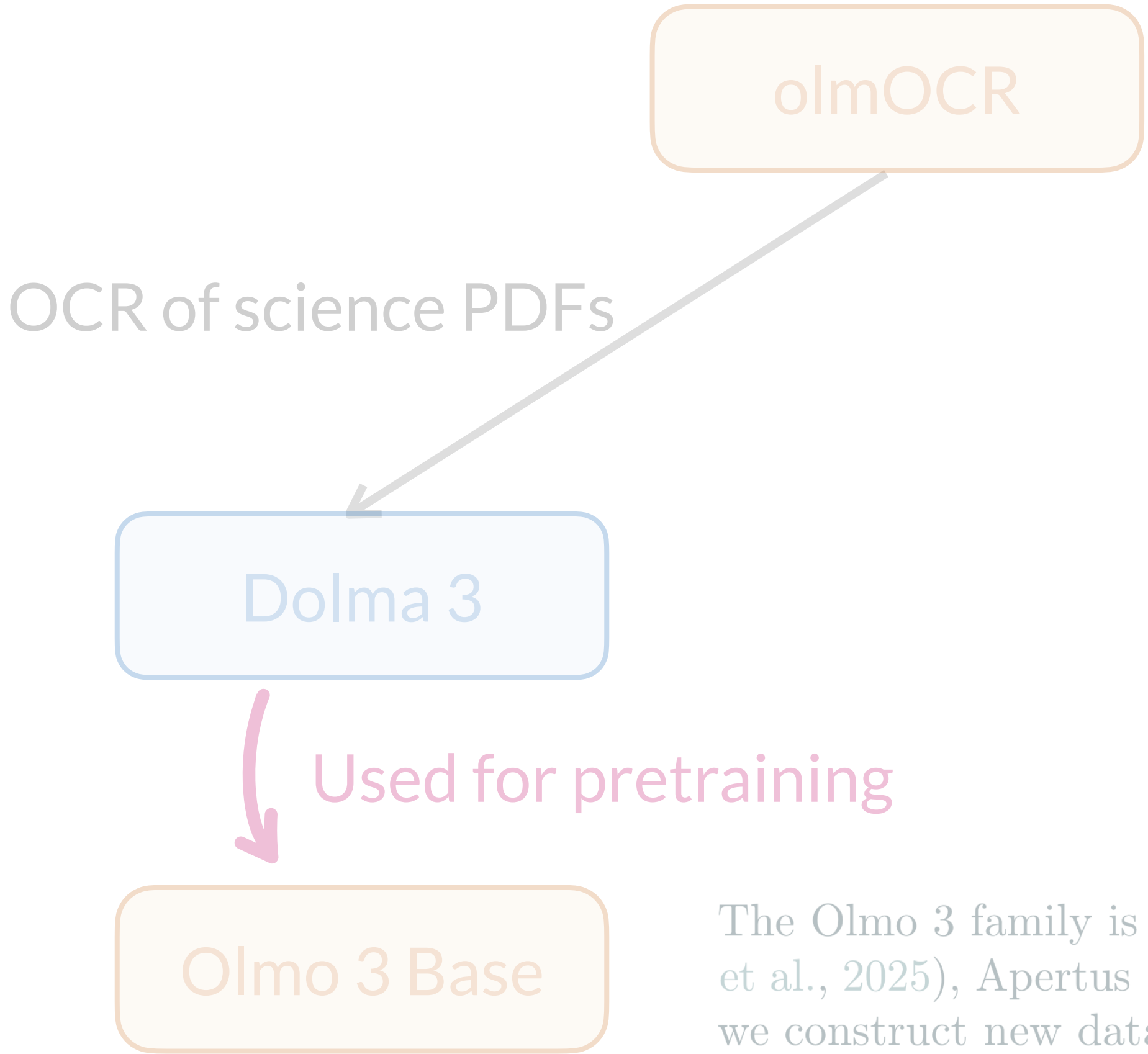
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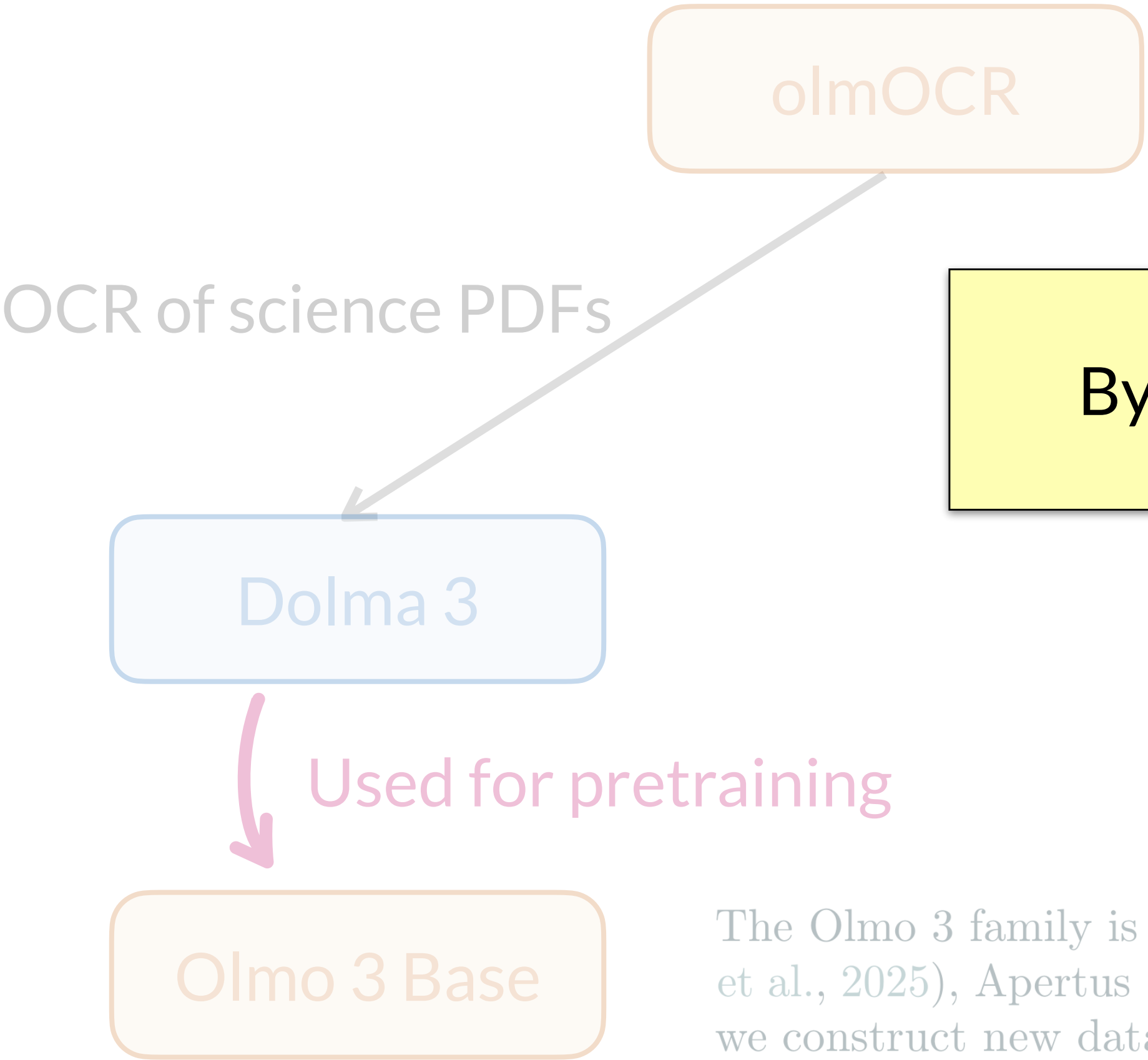
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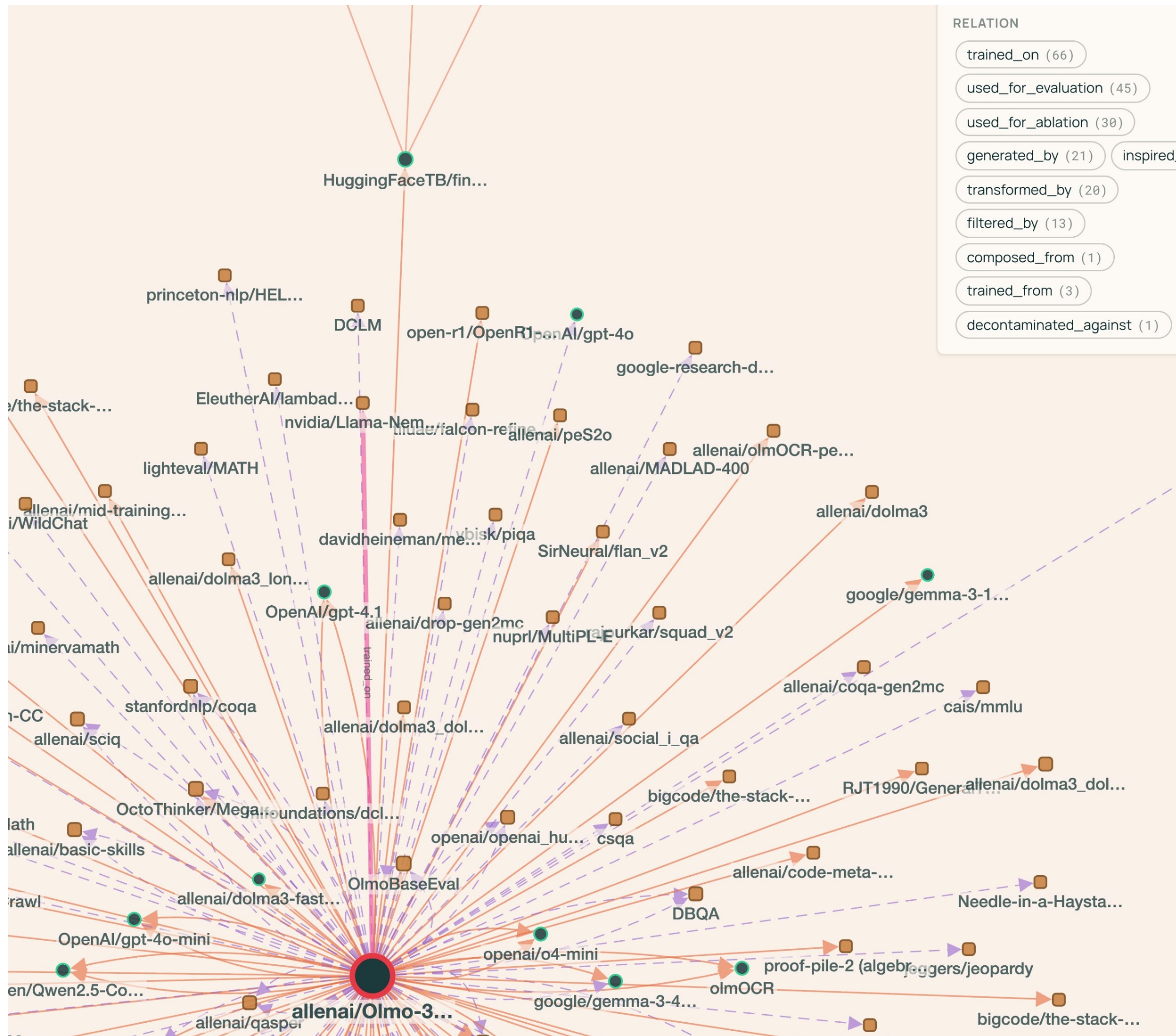
By scaling this effort ...

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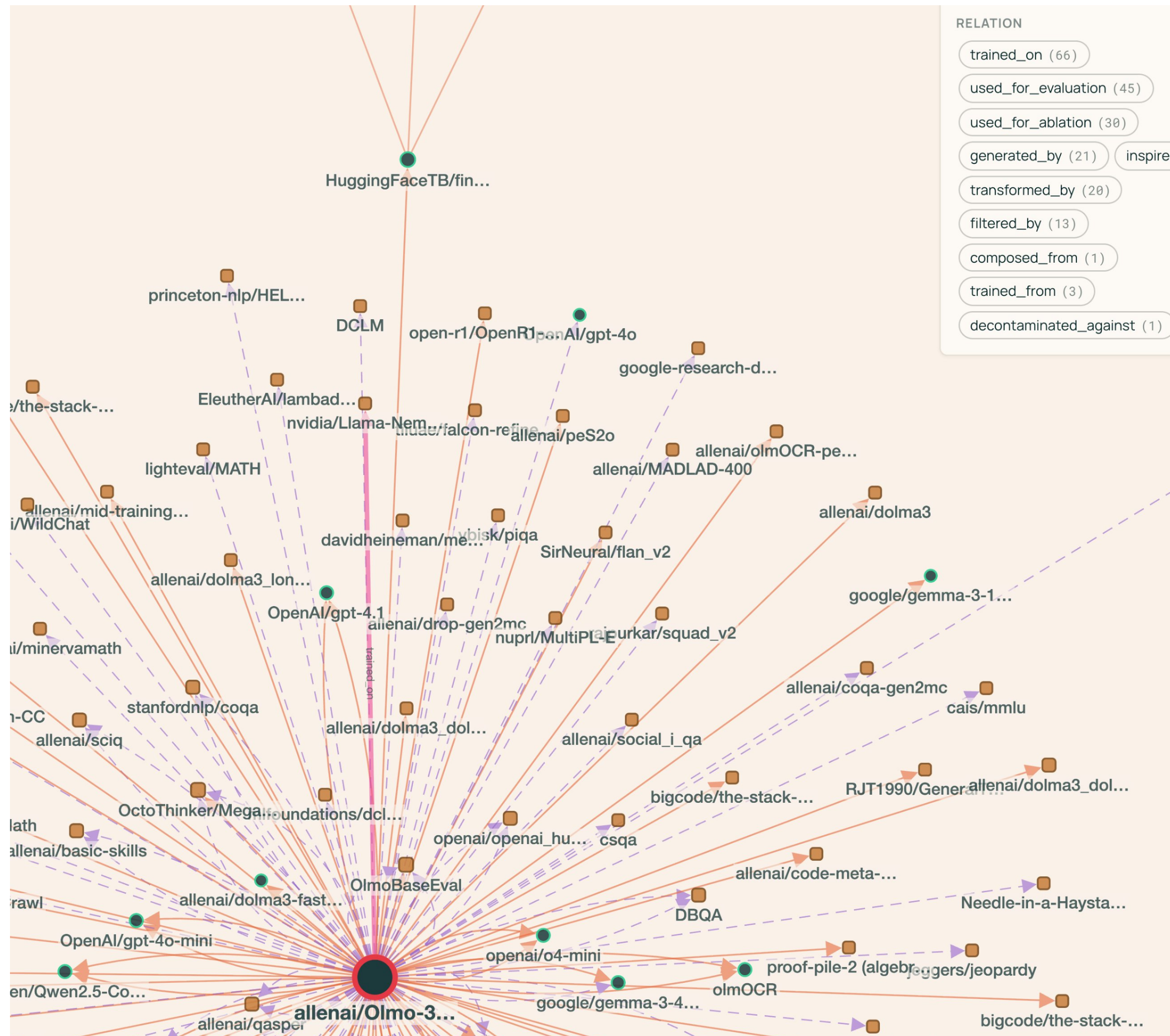
ModSleuth: Reconstructing **dependency** graphs



● circle = model ■ square = dataset
— arrow = one documented dependency
Target Olmo 3 at the bottom centre;
depth grows outward.

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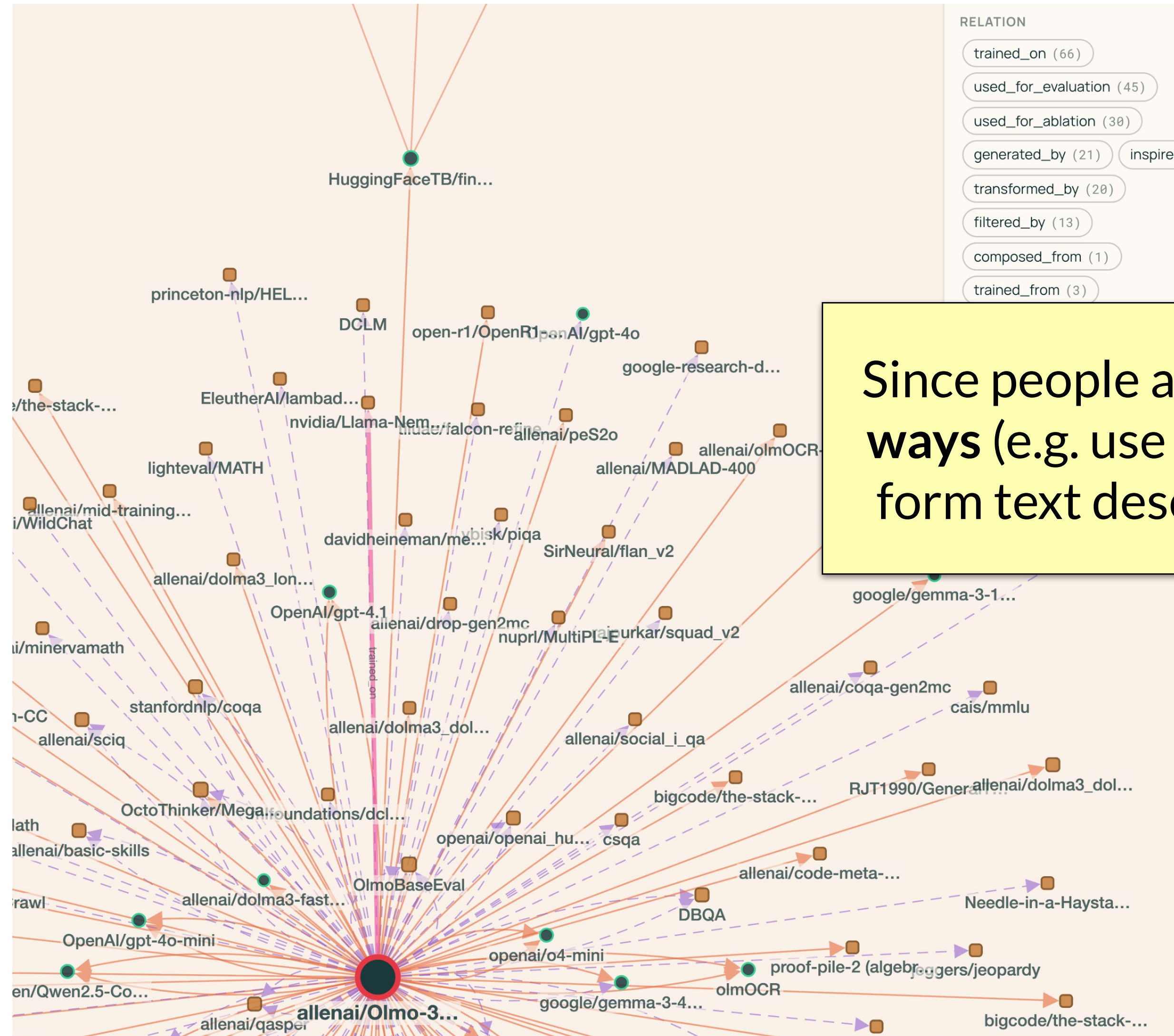
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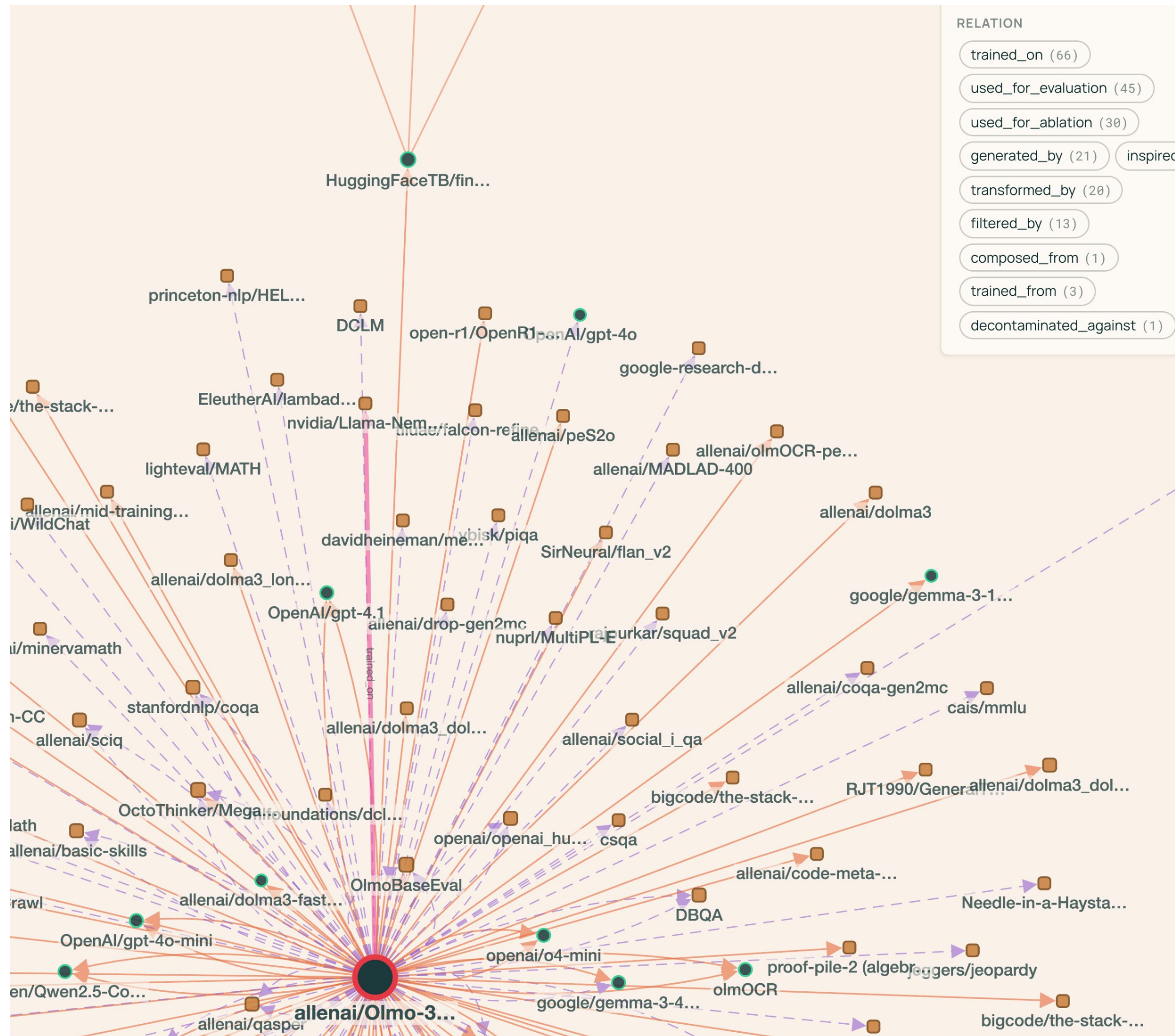
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Since people are using models in **more and more creative ways** (e.g. use olmOCR to process PDFs), we ask for free-form text description for a dependency to preserve info.

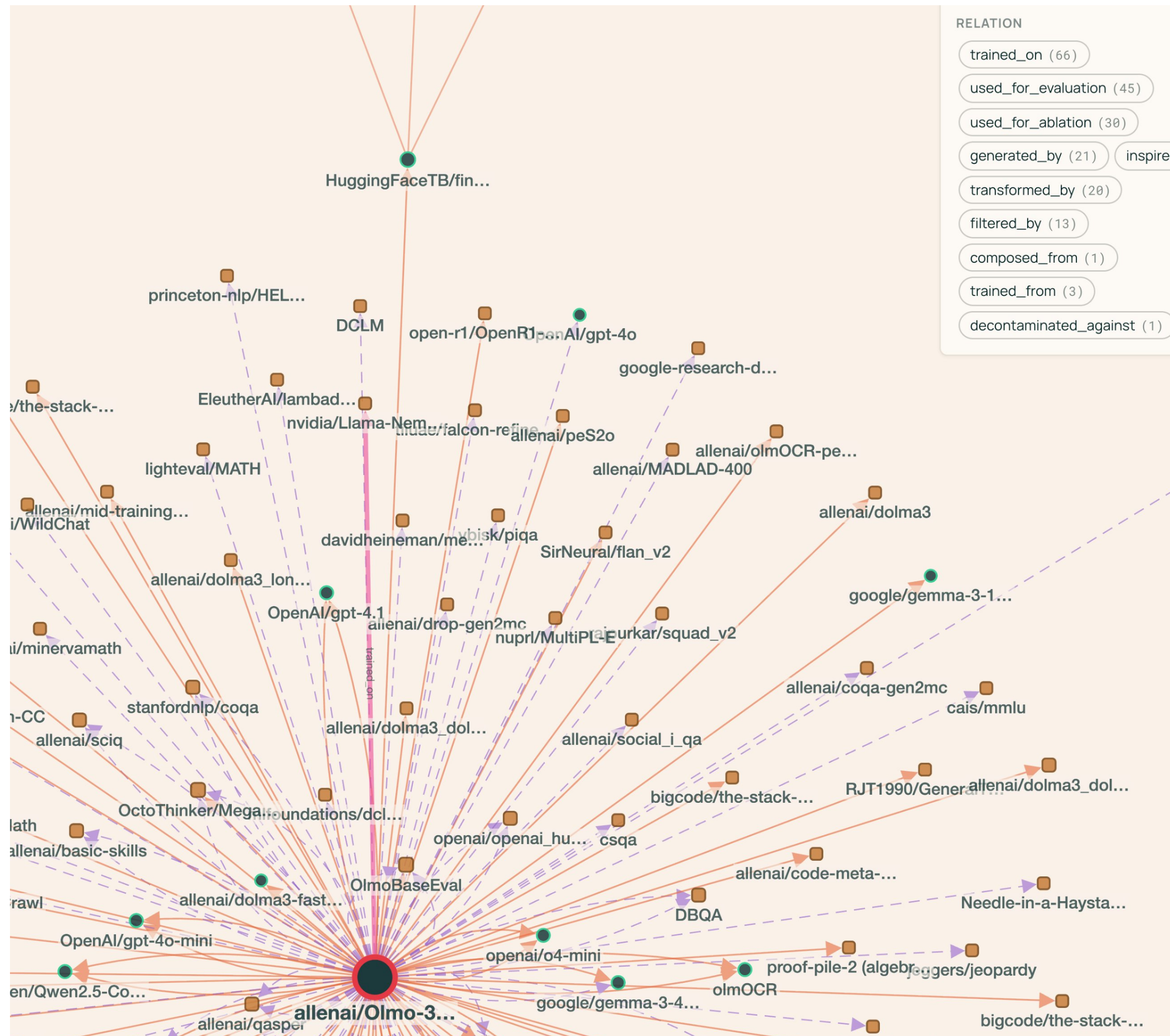
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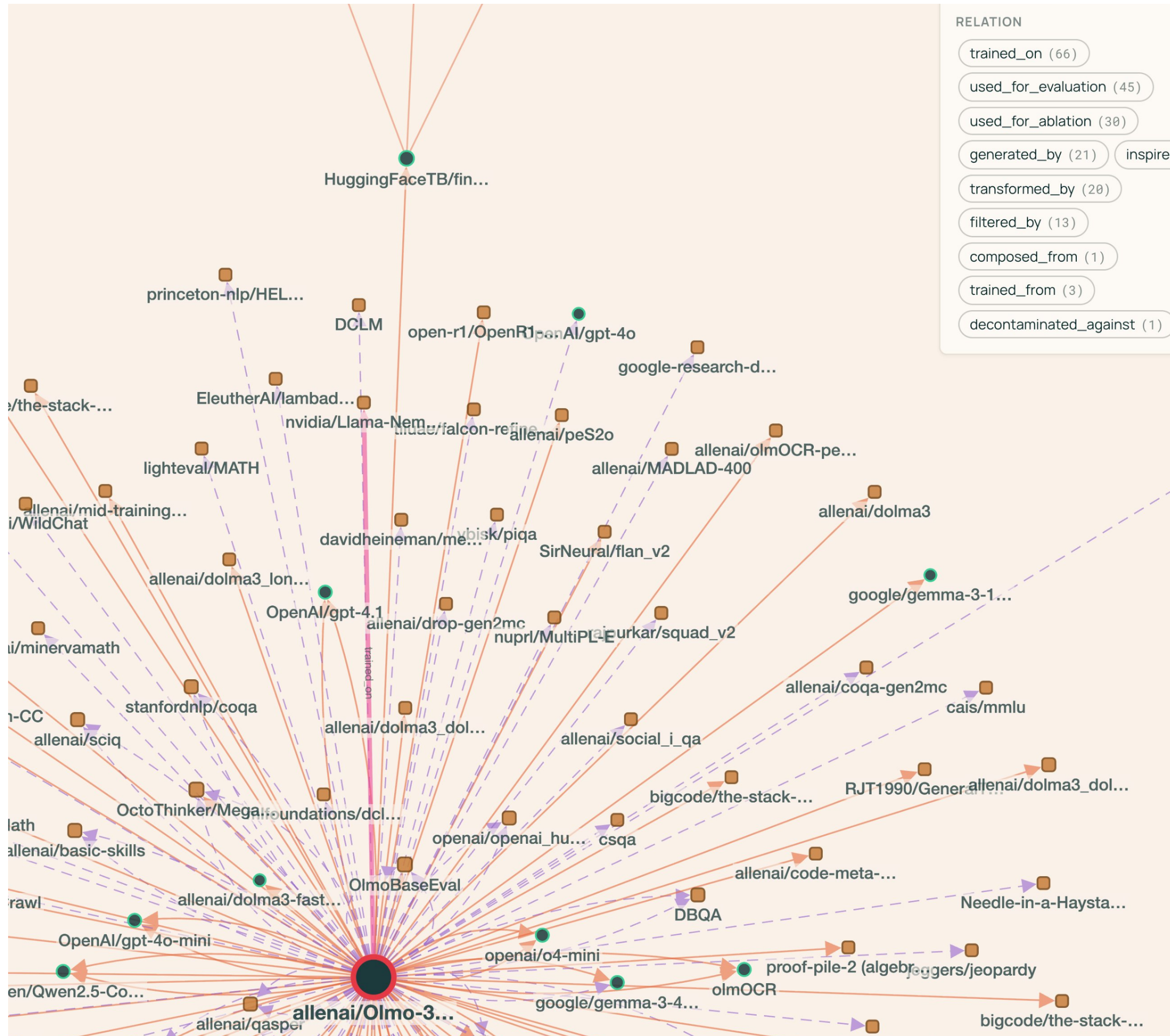
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Our task: **Recursively** reconstructs LLM **dependency graphs** from **public artifacts** with source-grounded evidence

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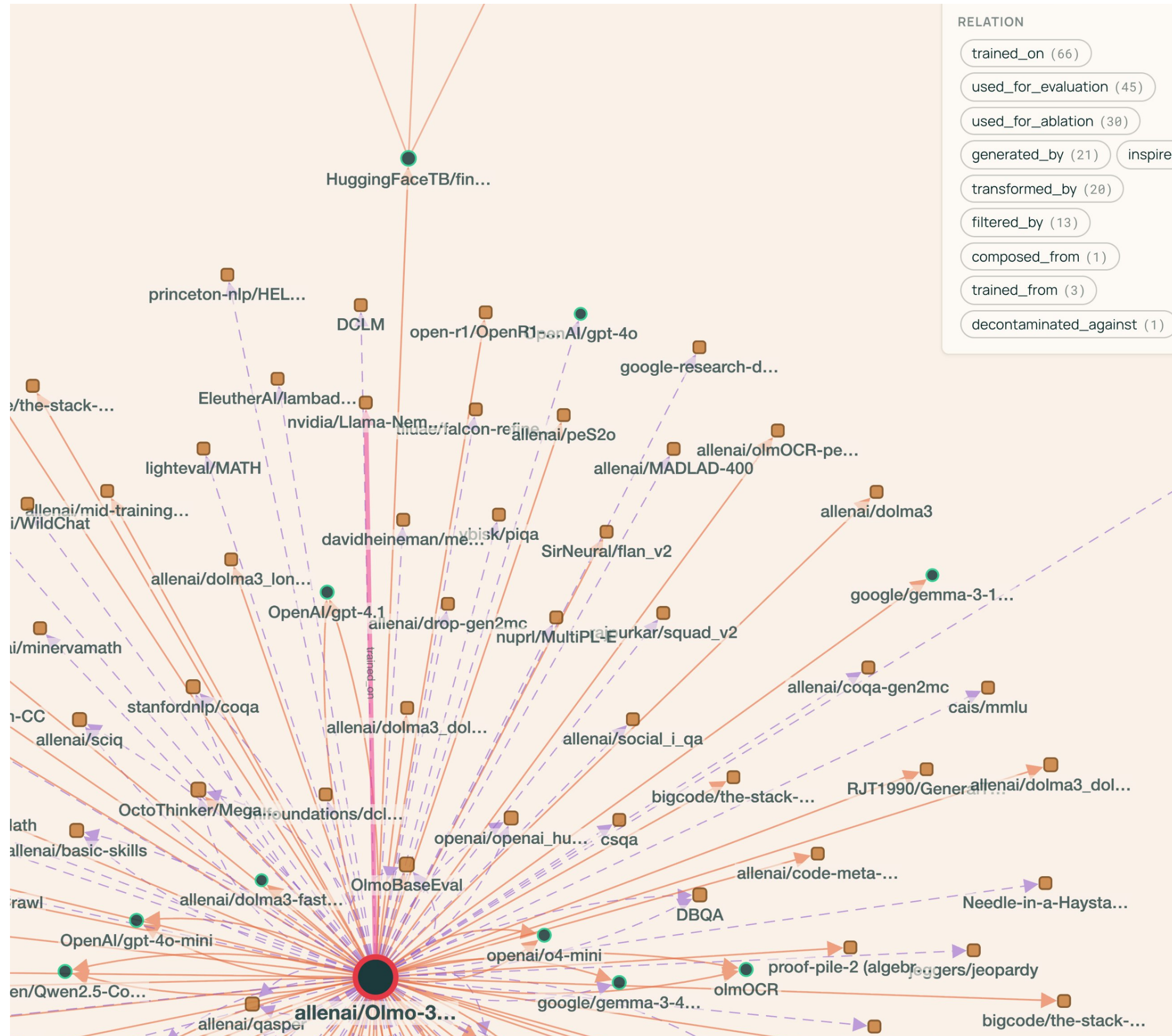


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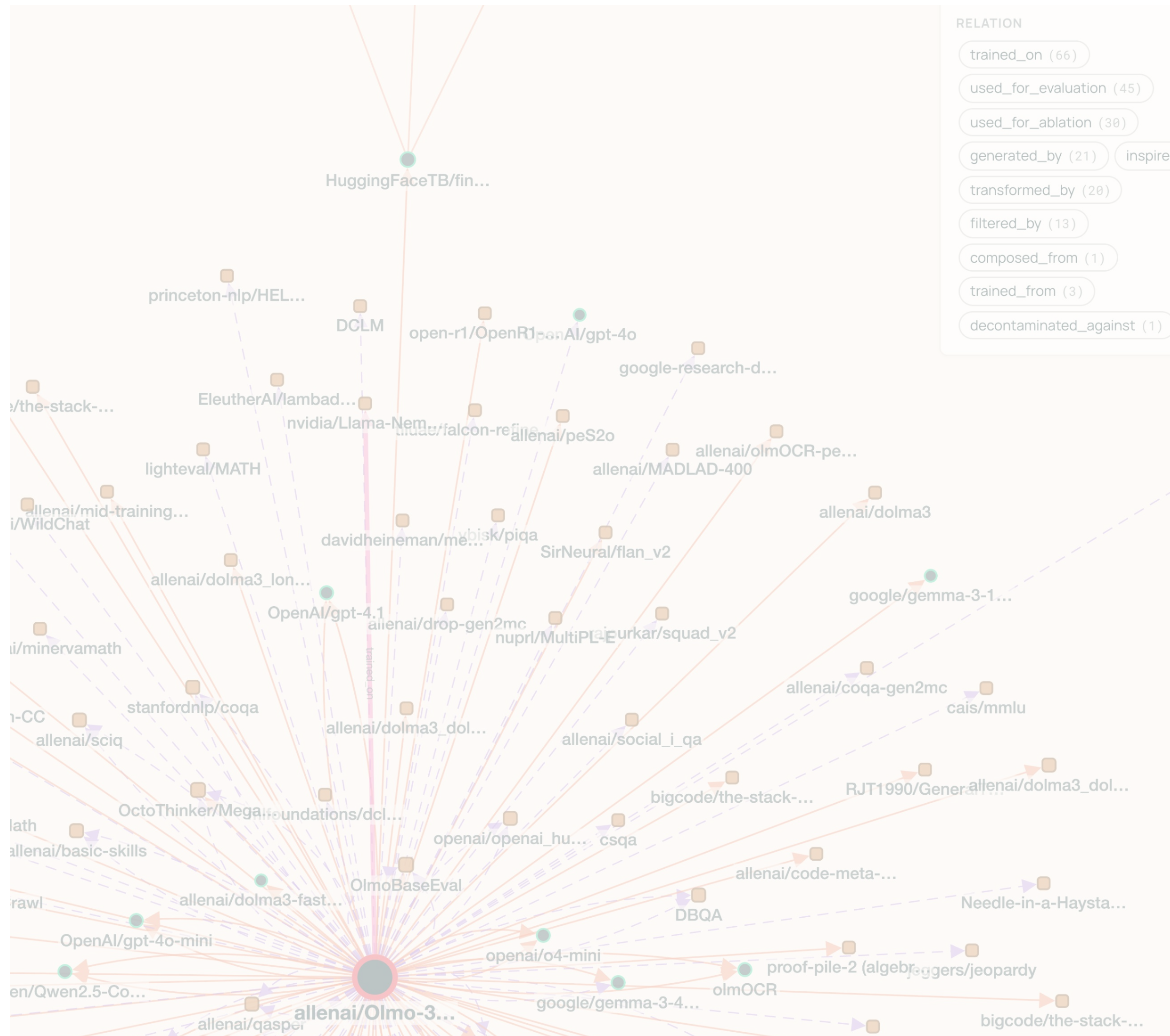
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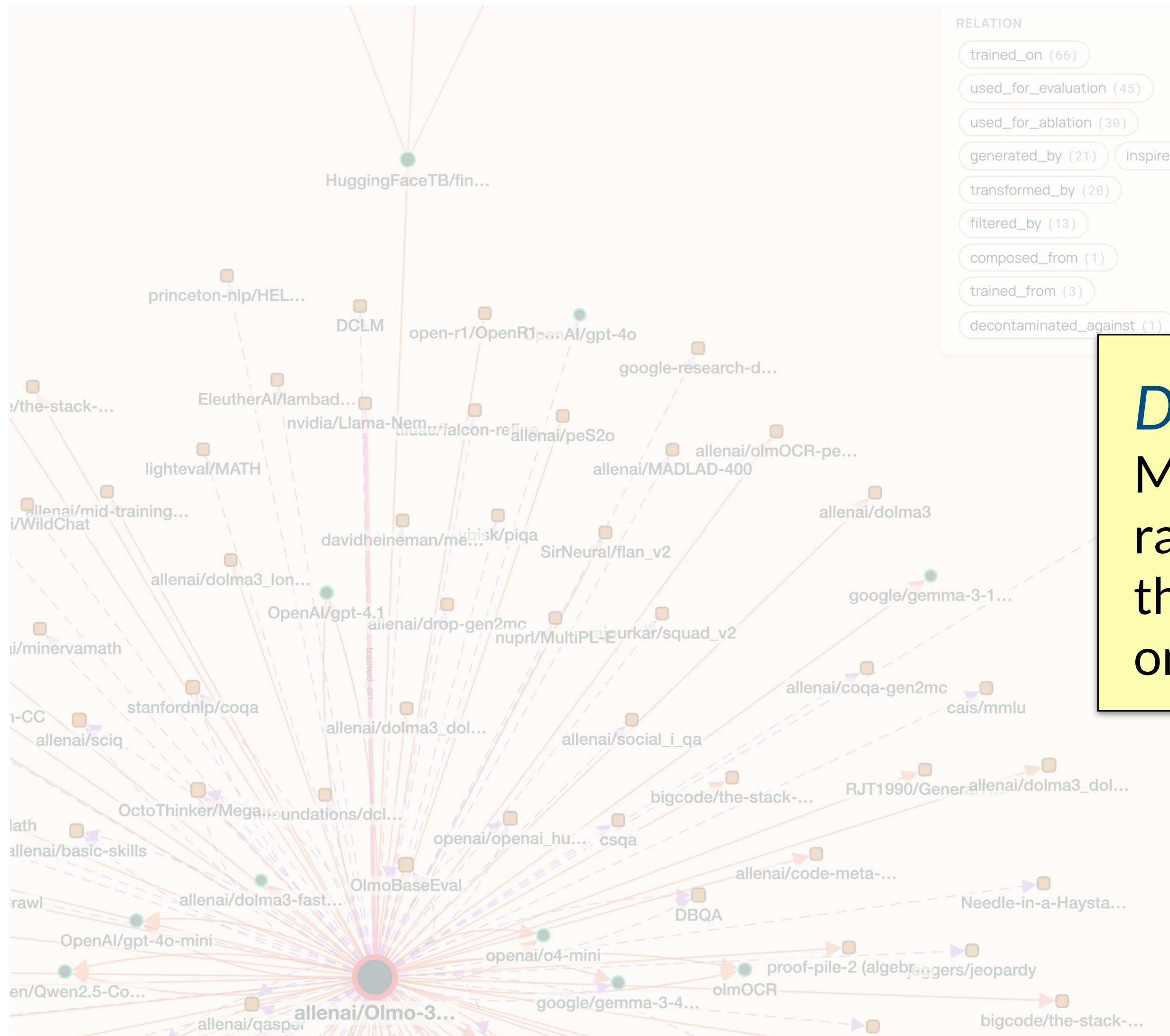
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ModSleuth: Reconstructing **dependency** graphs



Our task: **Recursively** reconstructs LLM **dependency graphs** from **public artifacts** with source-grounded evidence

Disclosure:

ModSleuth identifies **declared** dependencies rather than **true** dependencies, meaning that the dependencies we detect likely represent only **a lower bound** on the actual dependencies.

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Talk Overview

1. What counts as a dependency, and why is tracing them hard?

Much more than a list of names! Every dependency enters through some operations (generating, filtering), many hops upstream, documented in scattered and ambiguous sources.

2. Can we *automatically* and *reliably* recover the dependency graph from public artifacts?

Yes! ModSleuth, an agentic system we developed, recursively expands the graph and grounds every edge in source evidence—recovering 3x more verified dependencies than baselines.

3. What do the recovered graphs reveal?

Plenty that no single page shows: hidden upstream models, license terms riding along multiple hops, benchmarks on both sides of training and eval, etc.

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expands the graph and grounds dependencies than baselines.

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Let's trace Olmo 3 by hand
to see the challenges!

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Starting Point

Pre-training

Post-training

Evaluation

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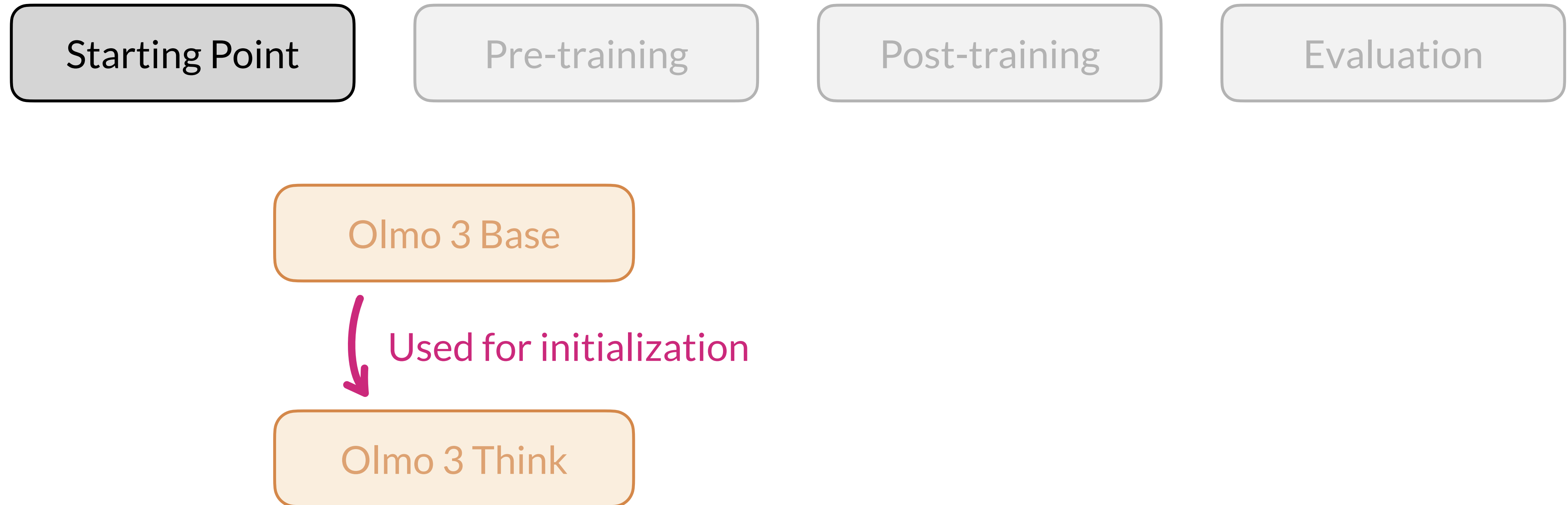
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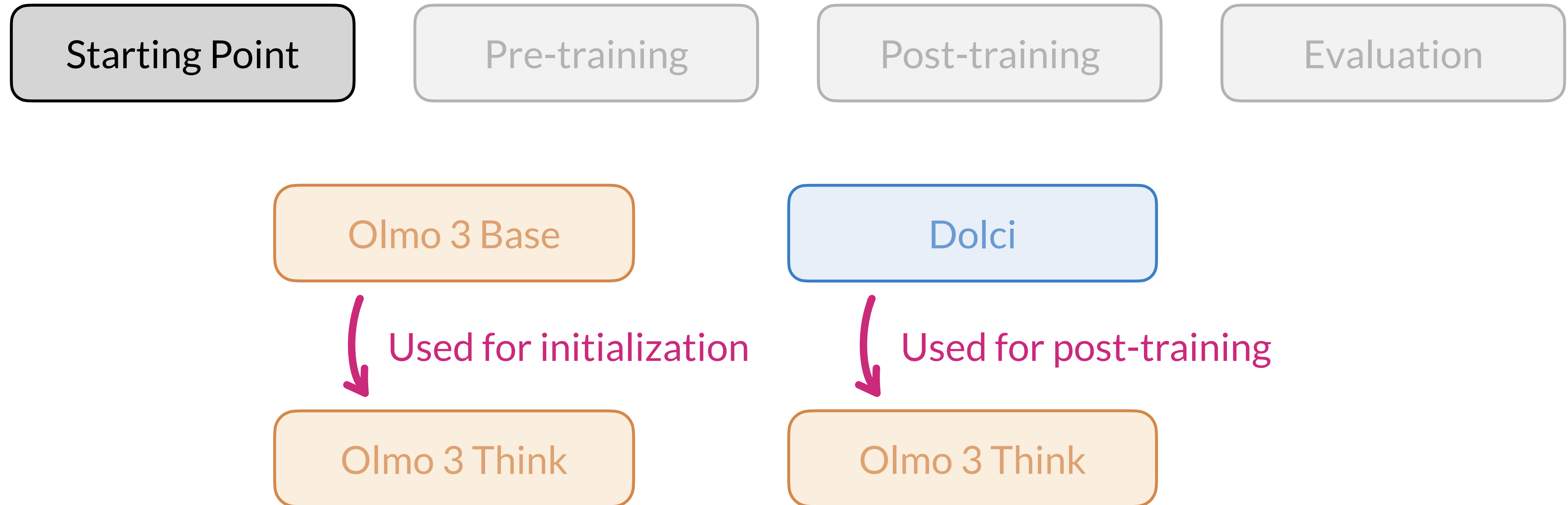
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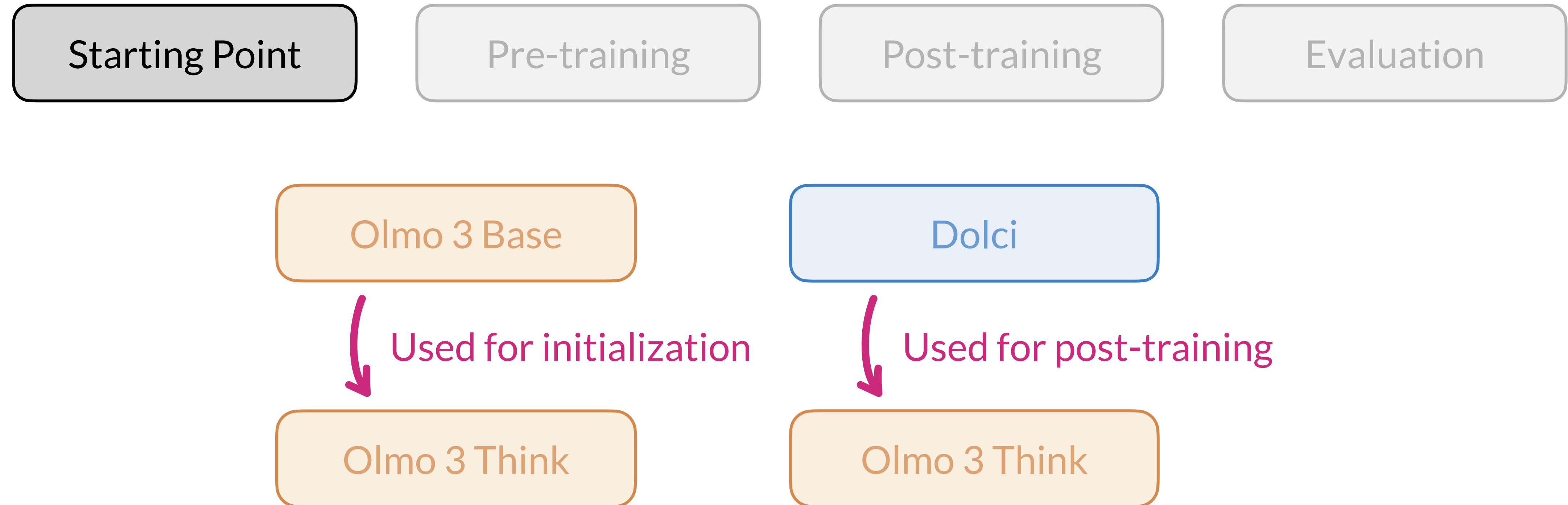
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These are the most obvious and widely-discussed forms of dependencies. However ...

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Olmo 3 Base



Used for initialization

Olmo 3 Think

Let's trace Olmo 3 by hand!

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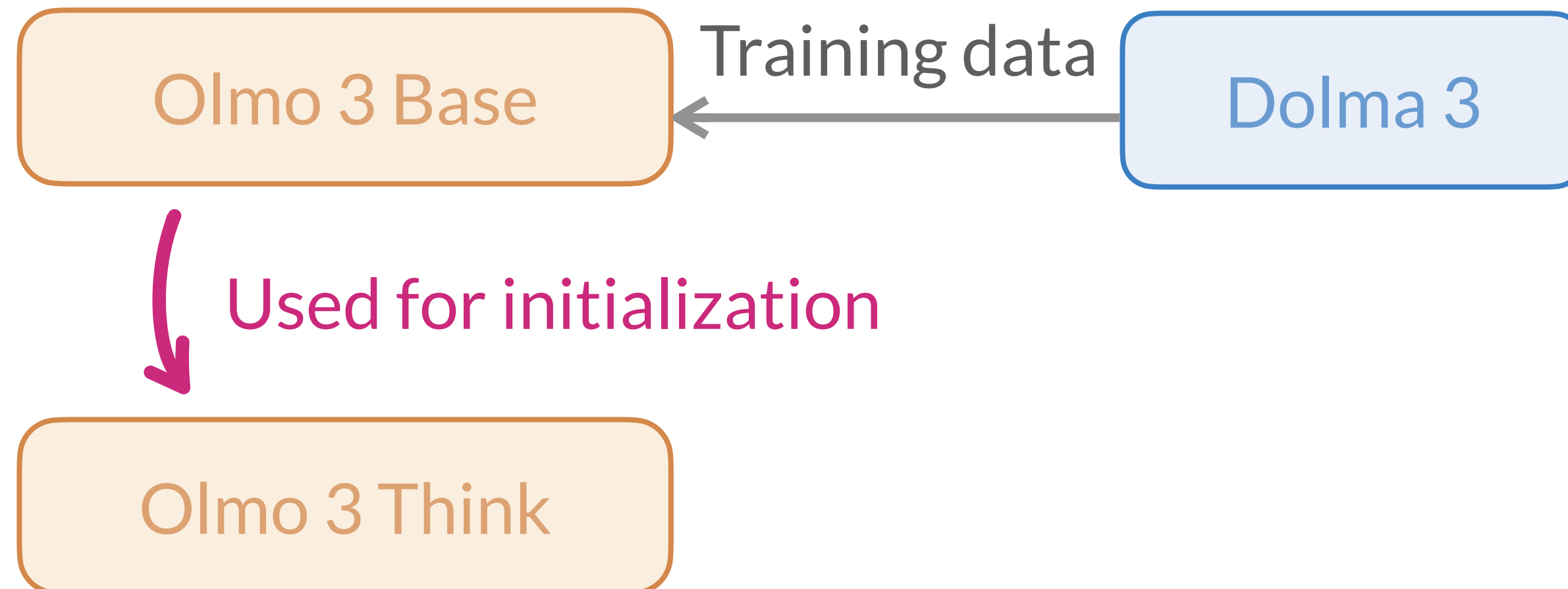
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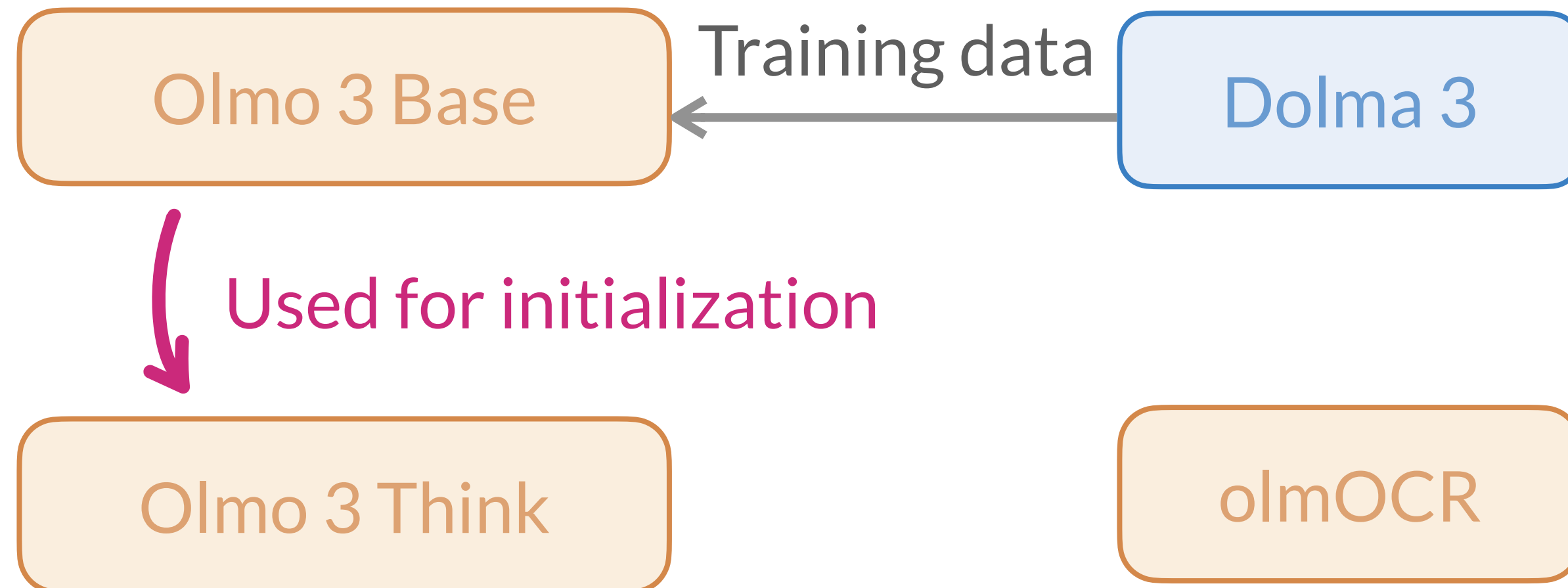
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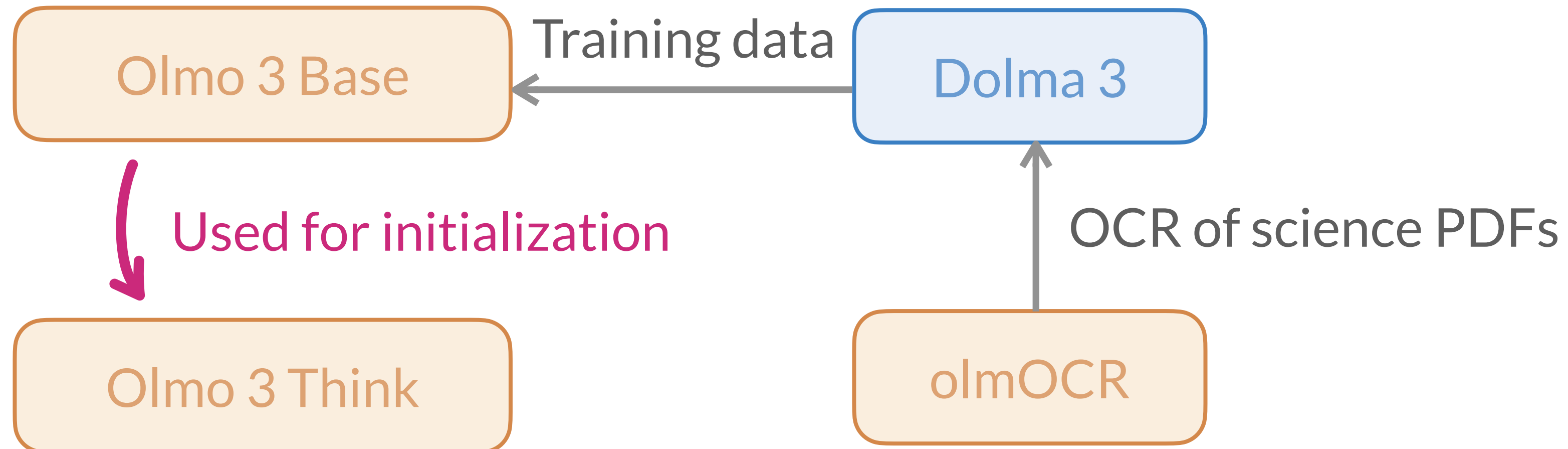
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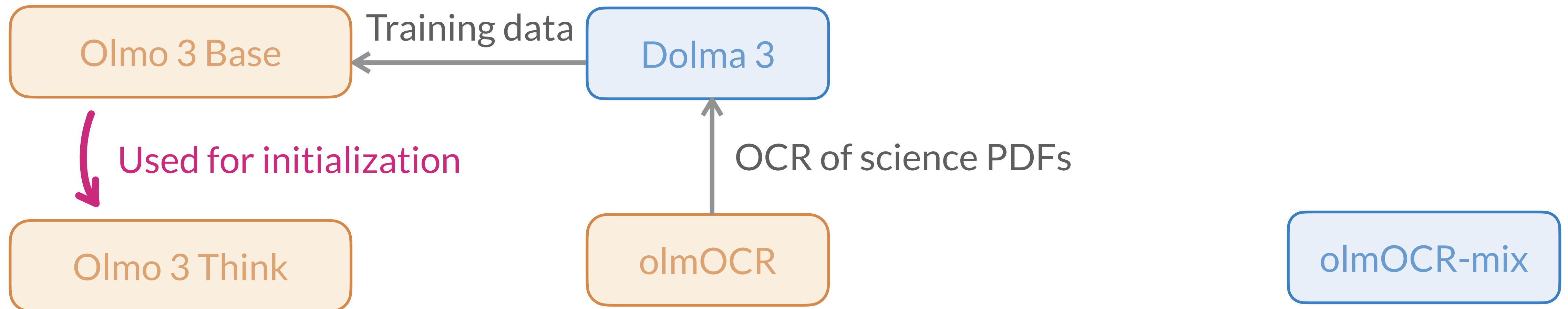
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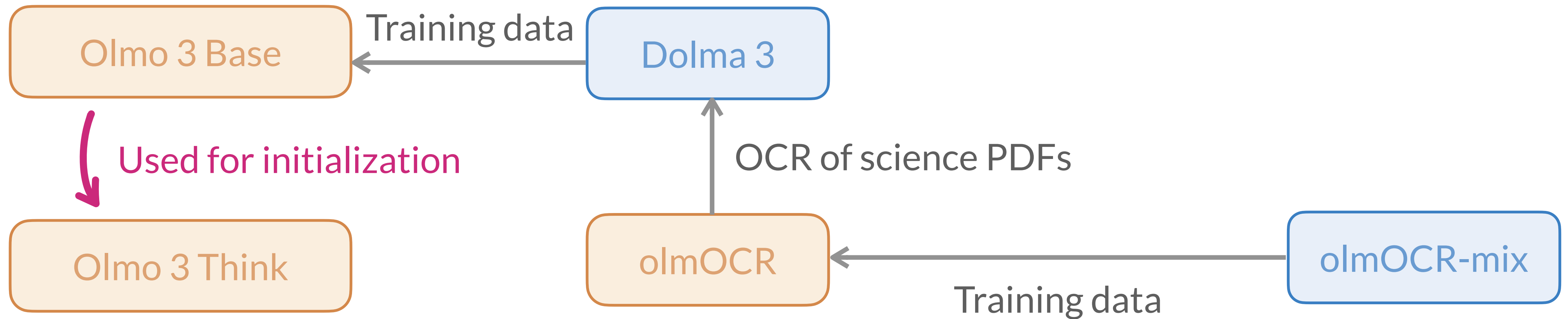
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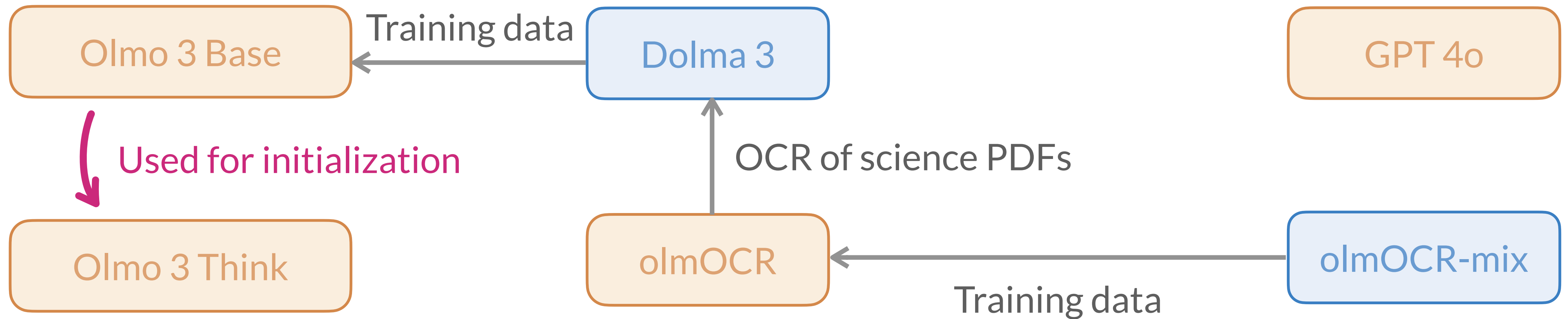
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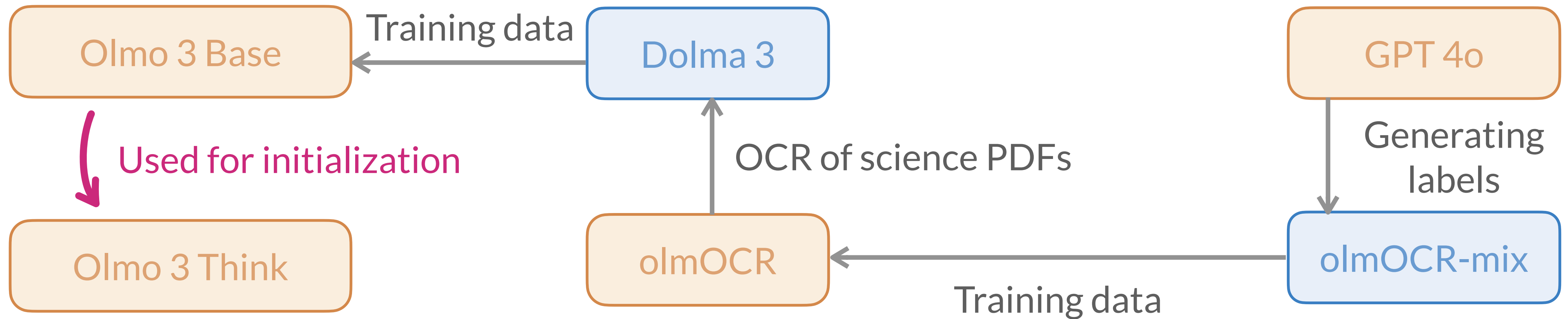
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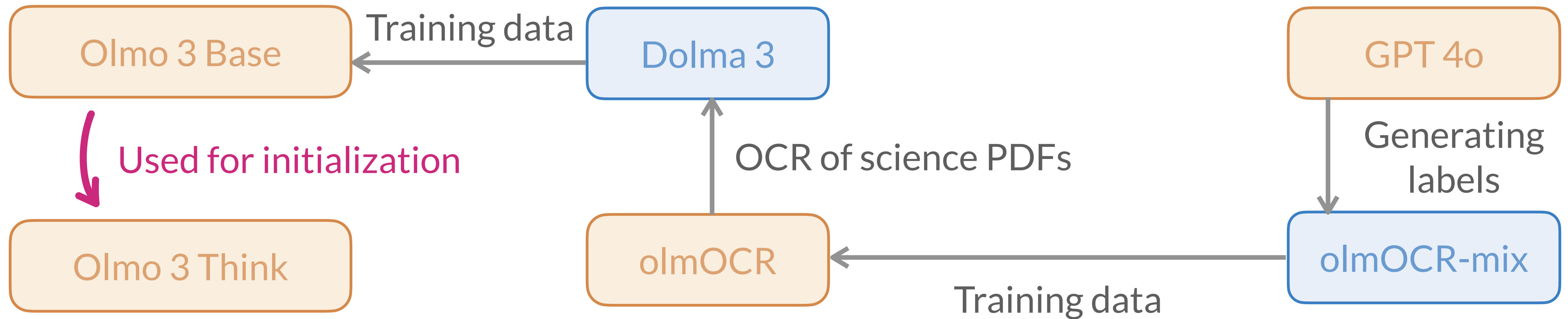
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Dependencies are (1) multi-hop (2) multi-type



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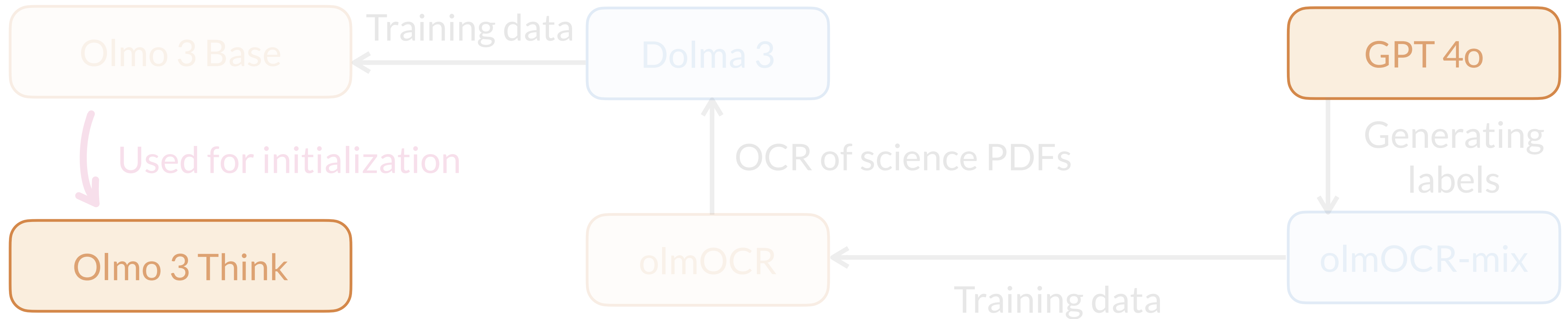
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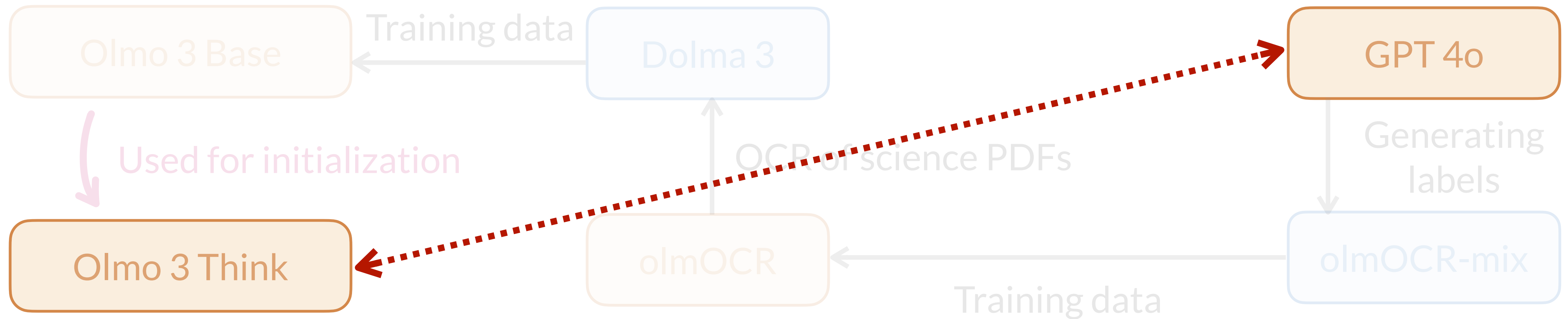
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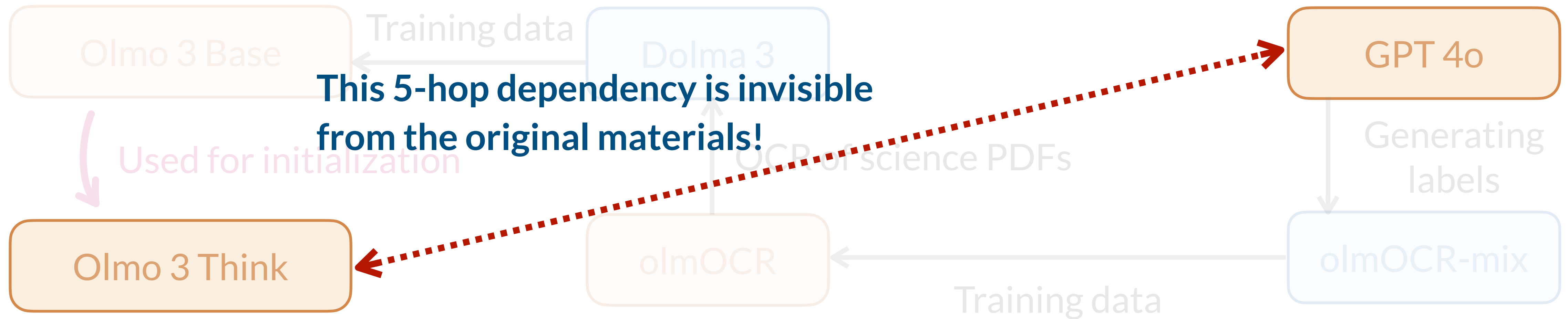
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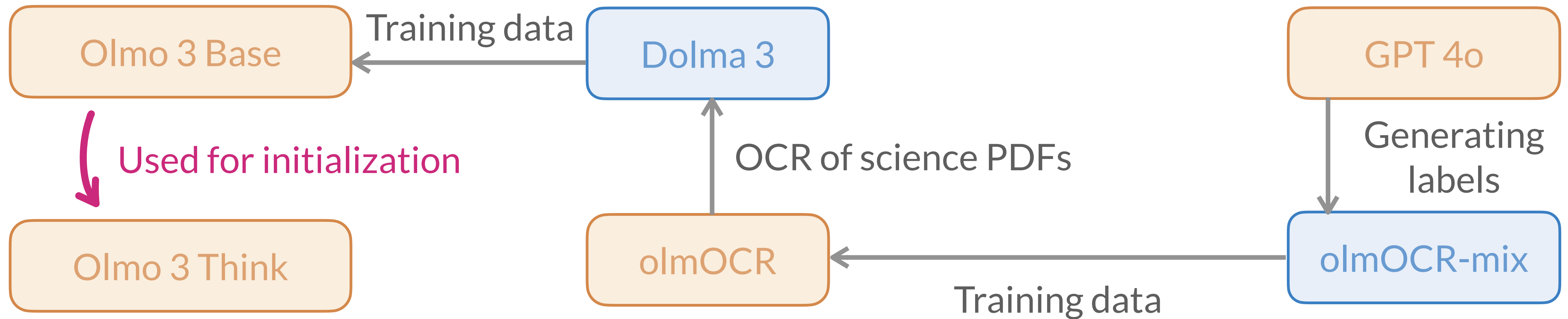
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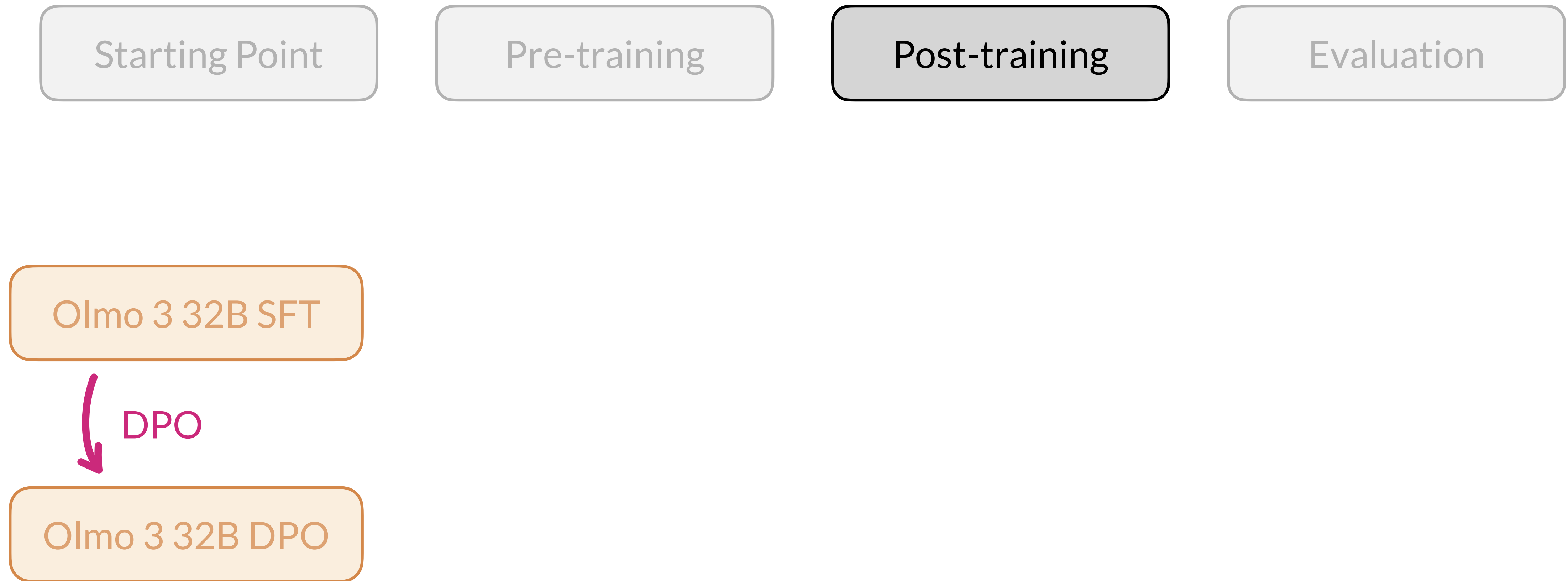
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Olmo 3 32B SFT



Olmo 3 32B DPO



To construct DOLCI THINK DPO, we compile a large pool of prompts covering a wide range of datasets and skills (see Table 19) and synthesize chosen and rejected responses to exhibit capability deltas. Following the delta-learning heuristic (Geng et al., 2025), for each prompt x , we simply decode a chosen completion y_c from one model (Qwen 3 32B, thinking) and a rejected completion y_r from an overall weaker model (Qwen 3 0.6B, thinking) to construct a consistent contrast.³²

Let's trace Olmo 3 by hand!

Starting Point

Pre-training

Post-training

Evaluation

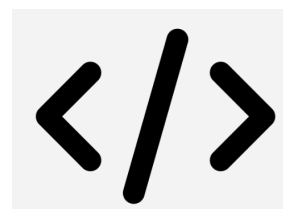
Olmo 3 32B SFT

DPO

Olmo 3 32B DPO



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`github.com/allenai/open-instruct/blob/
main/scripts/train/olmo3/32b_instruct_dpo.sh`

```
--use_slow_tokenizer False \  
--mixer_list allenai/olmo-3-preference-mix-deltas_reasoning-scottmix-DECON-keyword-ftd-topic-ftd-dedup5_take2 1.0 \  
--max_train_samples 200000 \  
--skip_cache \  
--zero_stage 3 \  
--max_seq_length 8192 \  
--per_device_train_batch_size 1 \  
--gradient_accumulation_steps 1 \  

```

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Dependencies are (1) multi-hop (2) multi-type

DPO

Olmo 3 32B DPO

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Dependencies are (1) multi-hop (2) multi-type (3) scattered across sources

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11 DATASET_MIXER_LIST=""
12 allenai/olmo-3-pref-mix-deltas-complement2-DECON-tpc-kwd-ch-dedup5-lbc100-grafmix-unbal 125000
13 allenai/dpo-yolo1-200k-gpt4.1-2w2s-maxdelta_reje-426124-rm-gemma3-kwd-ftd-ch-ftd-topic-ftd-dedup5-lbc100 125000
14 allenai/general_responses_dev_8maxturns_truncate-9fbef8-enrejected-kwd-ftd-cn-ftd-topic-filt-lb100 1250
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GPT-4.1-2025-04-14?

Let's trace Olmo 3 by hand!

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GPT-4.1-2025-04-14?

Gemma3 1B? 4B? 12B?

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What is 2w2s?

GPT-4.1-2025-04-14?

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This will become a big issue when we are trying to merge the nodes and edges extracted from different sources.

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Post-training

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Olmo 3 Think (V2)

Olmo 3 Think (V1)

GSM8K

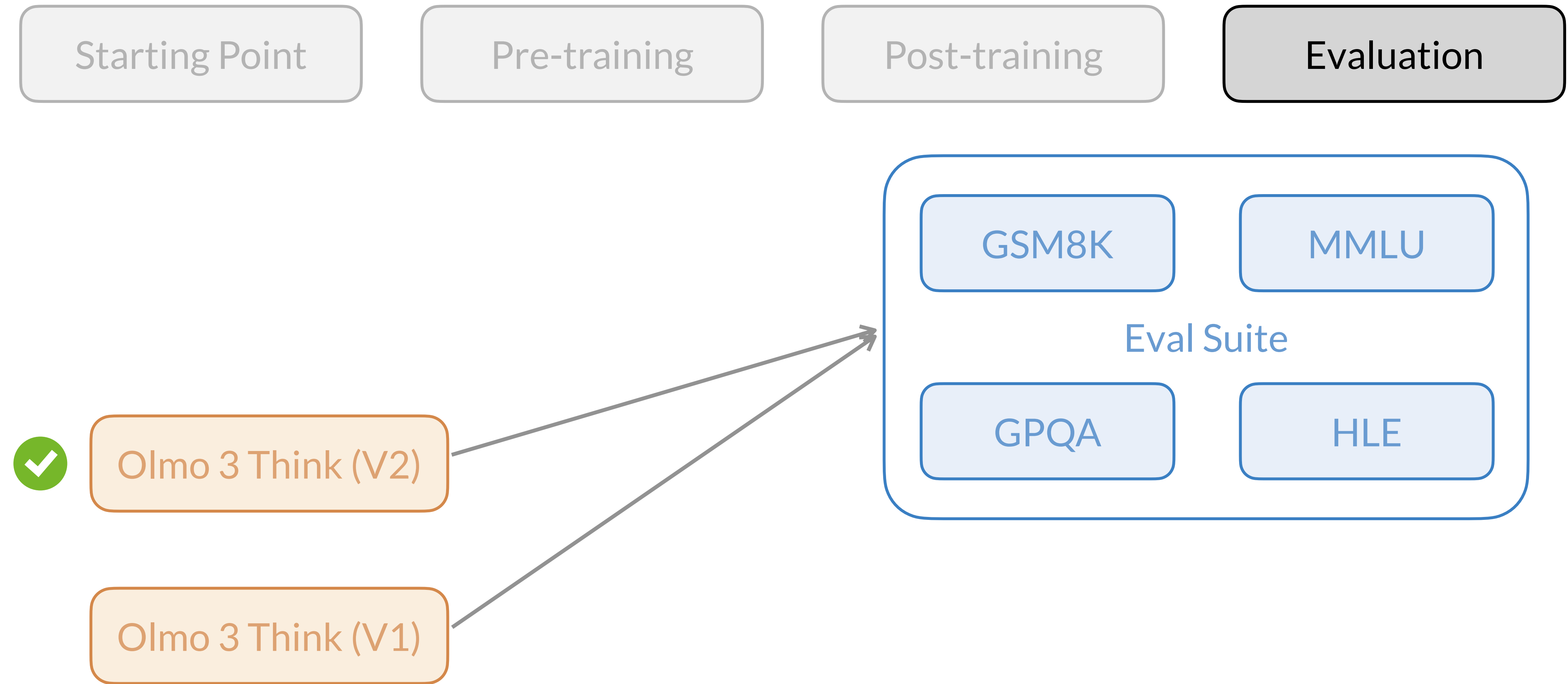
MMLU

Eval Suite

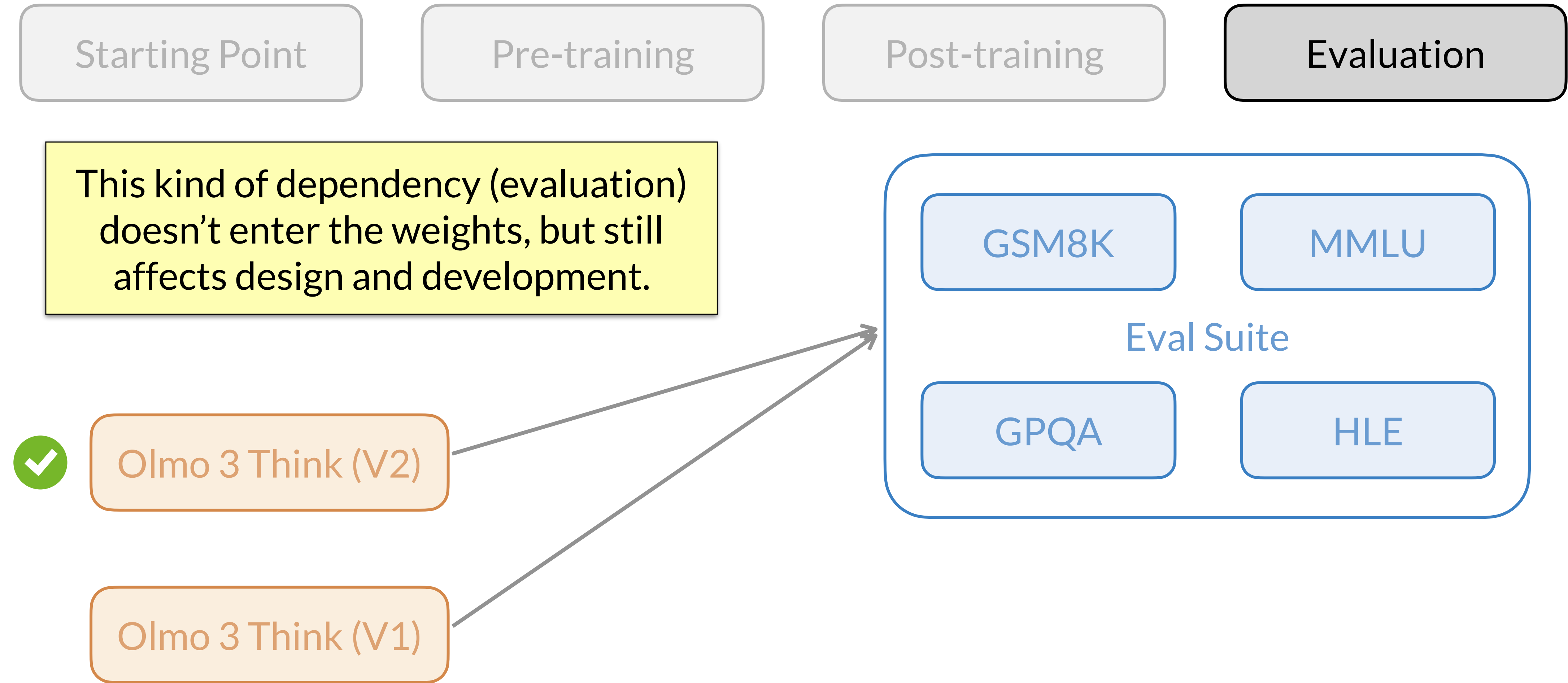
GPQA

HLE

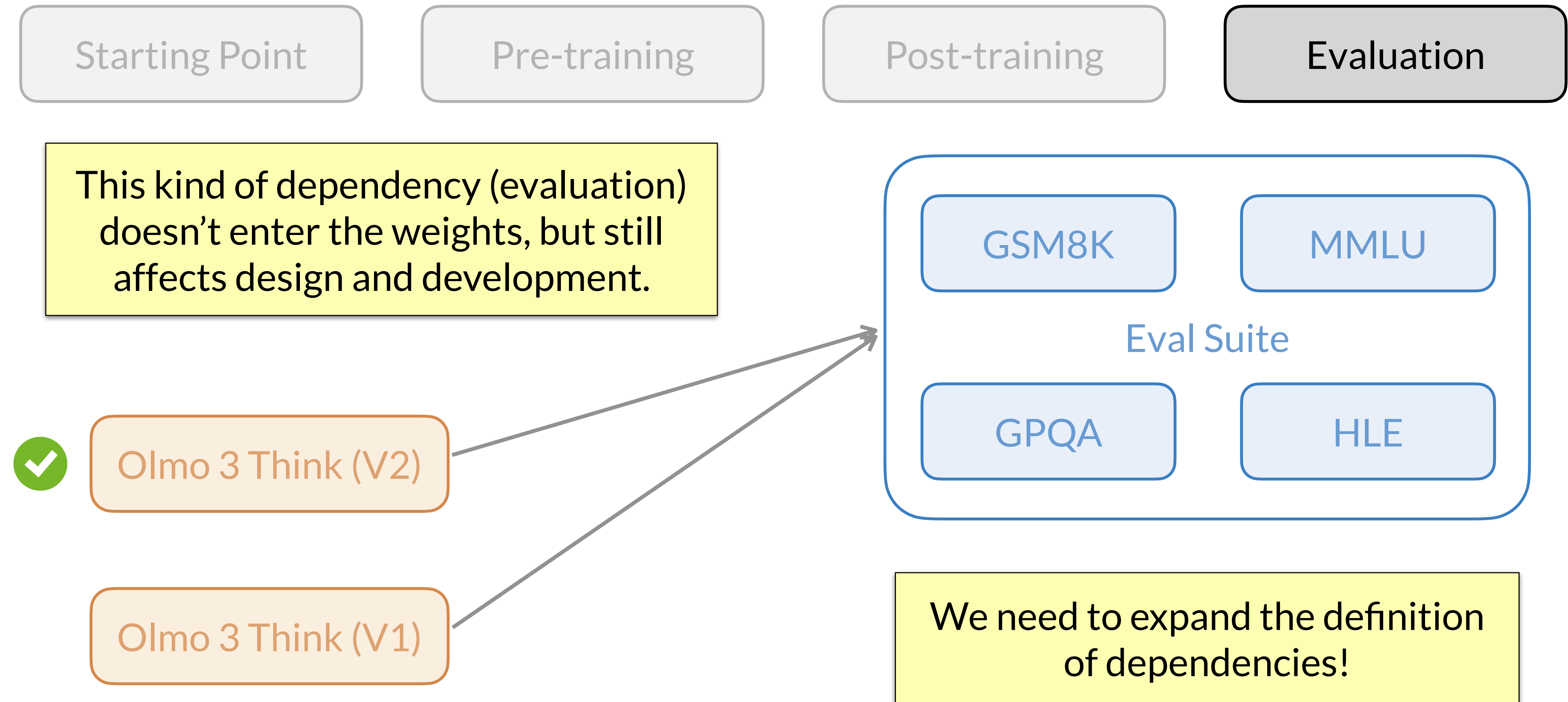
Let's trace Olmo 3 by hand!



Let's trace Olmo 3 by hand!



Let's trace Olmo 3 by hand!



Let's trace Olmo 3 by hand!

Starting Point

Pre-training

Post-training

Evaluation

This kind of dependency (evaluation) doesn't enter the weights, but still affects design and development

GSM8K

MMLU

Dependencies are (1) multi-hop (2) multi-type (3) scattered across sources (4) underspecified



Olmo 3 Think (V2)

Olmo 3 Think (V1)

We need to expand the definition of dependencies!

Let's trace Olmo 3 by hand!

Starting Point

Pre-training

Post-training

Evaluation

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GSM8K

MMLU

Dependencies are (1) multi-hop (2) multi-type (3) scattered across sources
(4) underspecified (5) inherently ambiguous to define



Olmo 3 Think (V2)

Olmo 3 Think (V1)

We need to expand the definition of dependencies!

Talk Overview

1. What counts as a dependency, and why is tracing them hard?

Much more than a list of names! Every dependency enters through some operations (generating, filtering), many hops upstream, documented in scattered and ambiguous sources.

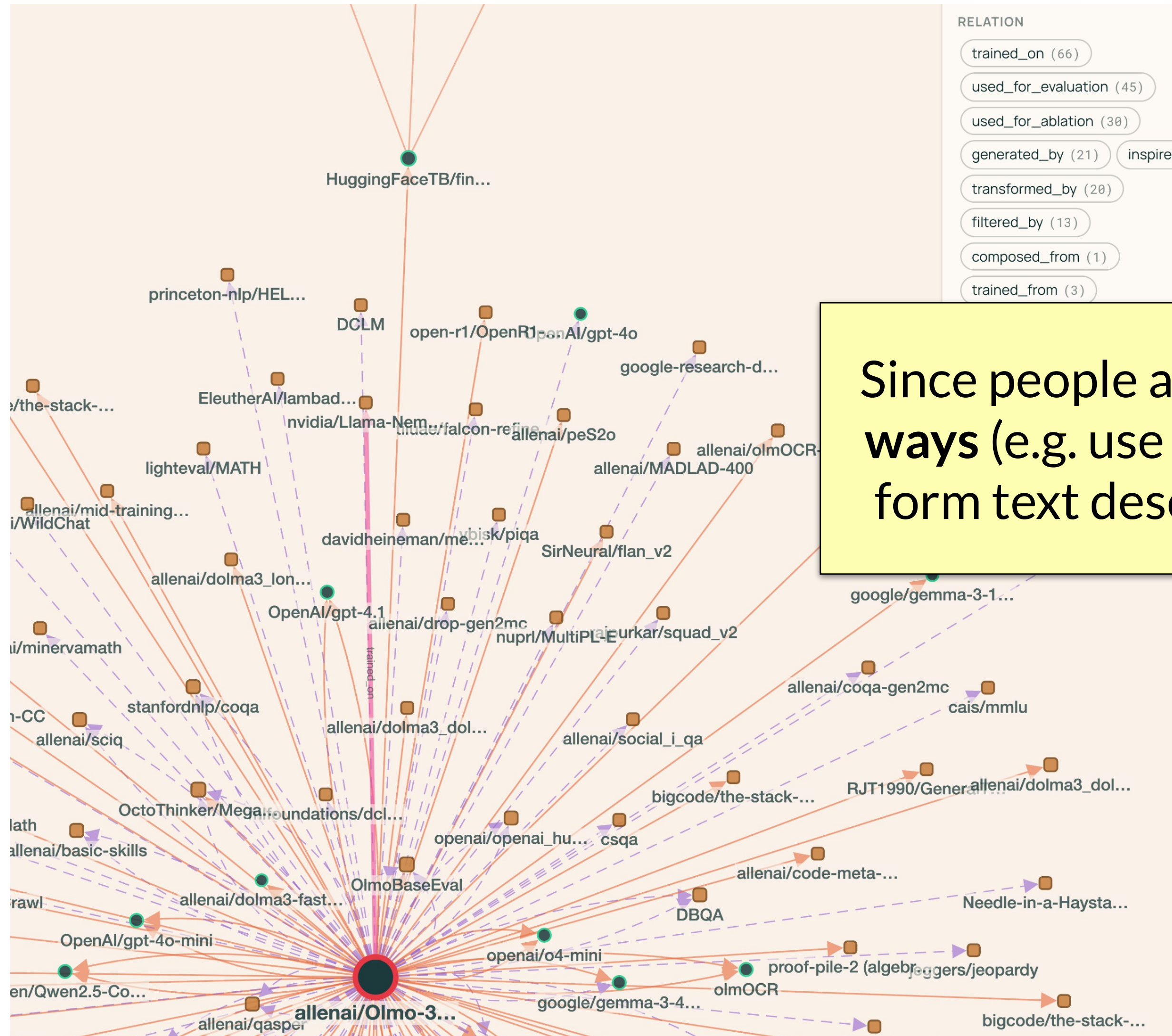
2. Can we *automatically* and *reliably* recover the dependency graph from public artifacts?

Yes! ModSleuth, an agentic system we developed, recursively expands the graph and grounds every edge in source evidence—recovering 3x more verified dependencies than baselines.

3. What do the recovered graphs reveal?

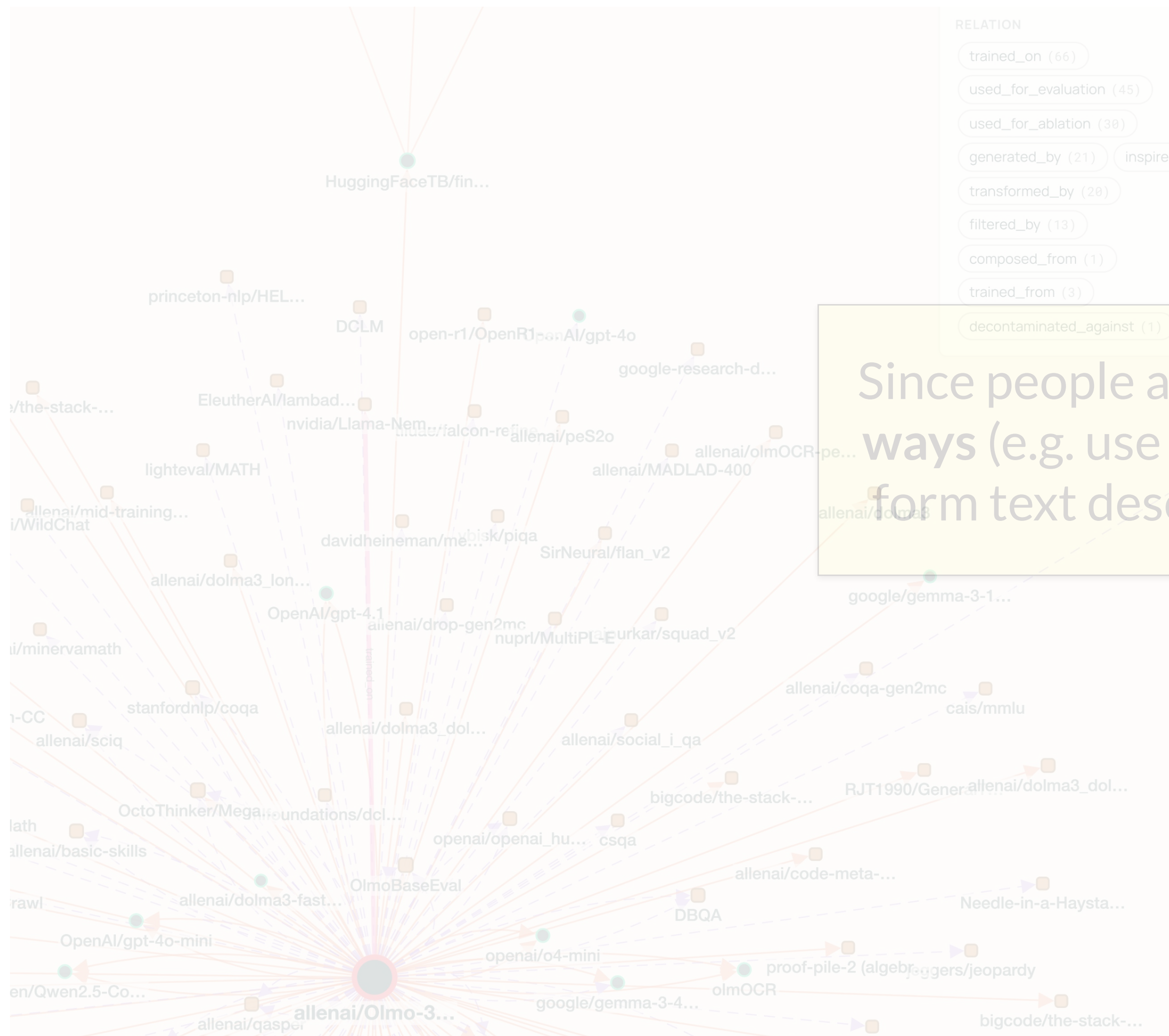
Plenty that no single page shows: hidden upstream models, license terms riding along multiple hops, benchmarks on both sides of training and eval, etc.

ModSleuth: Reconstructing **dependency** graphs



● circle = model ■ square = dataset
— arrow = one documented dependency
Target Olmo 3 at the bottom centre;
depth grows outward.

ModSleuth: Reconstructing **dependency** graphs



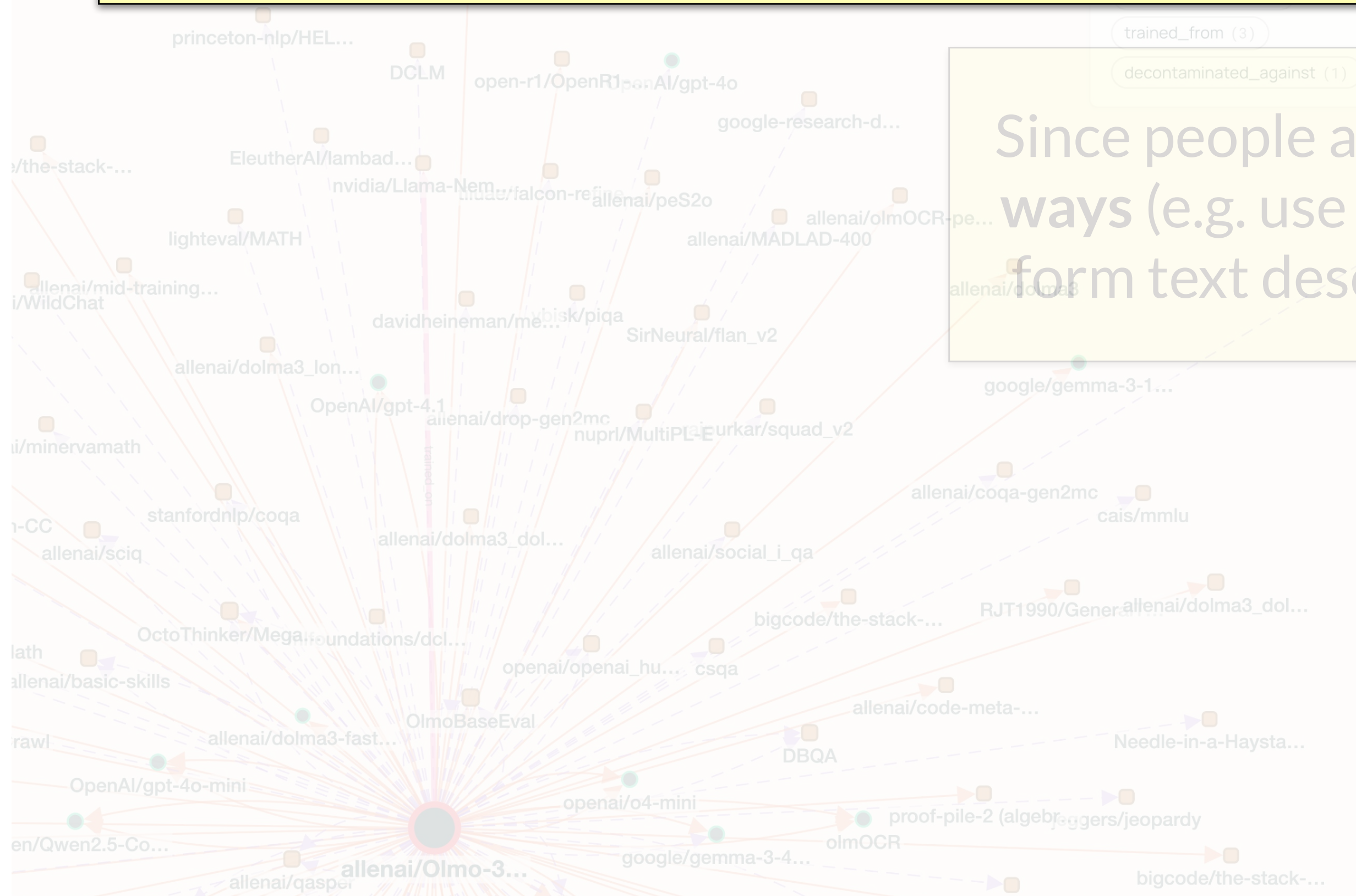
Since people are using models in more and more creative ways (e.g. use olmOCR to process PDFs), we ask for free-form text description for a dependency to preserve info.

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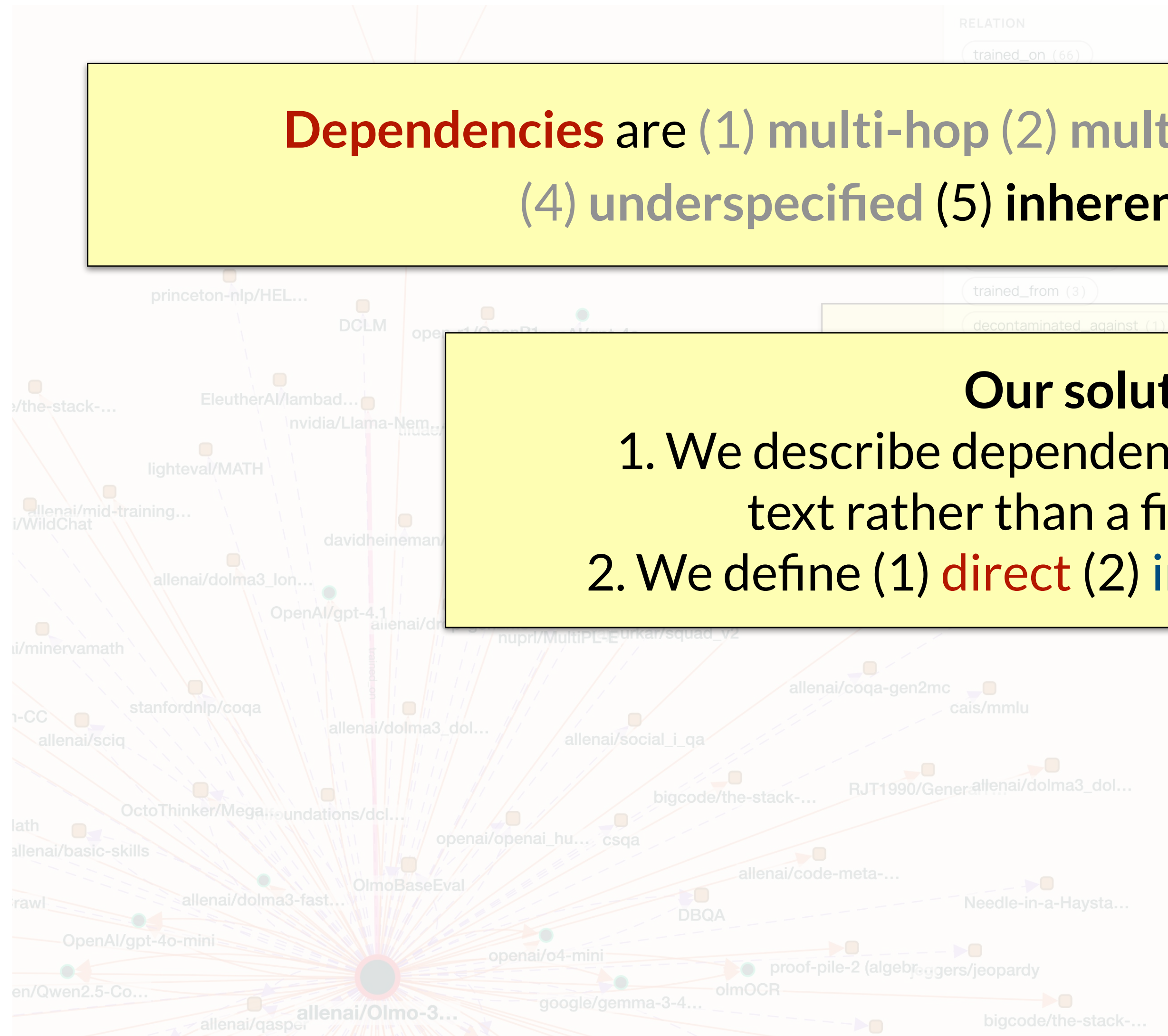
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Our solution:

1. We describe dependencies using free-form text rather than a fixed taxonomy
2. We define (1) **direct** (2) **indirect** dependencies



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Our solution:

1. We describe dependencies using free-form text rather than a fixed taxonomy
2. We define (1) **direct** (2) **indirect** dependencies

- (1) **Direct**: upstream artifact that affects the target model's training or weights
- (2) **Indirect**: upstream artifact that does not directly enter training, but nevertheless substantially influences development decisions

Design of ModSleuth

Design of ModSleuth

Let's trace Olmo-3-7B with ModSleuth!

Dependencies are (1) multi-hop (2) multi-type (3) **scattered across sources**
(4) underspecified (5) ~~inherently ambiguous to define~~

Let's trace Olmo-3-7B with ModSleuth!

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1 Source
Gathering

Let's trace Olmo-3-7B with ModSleuth!

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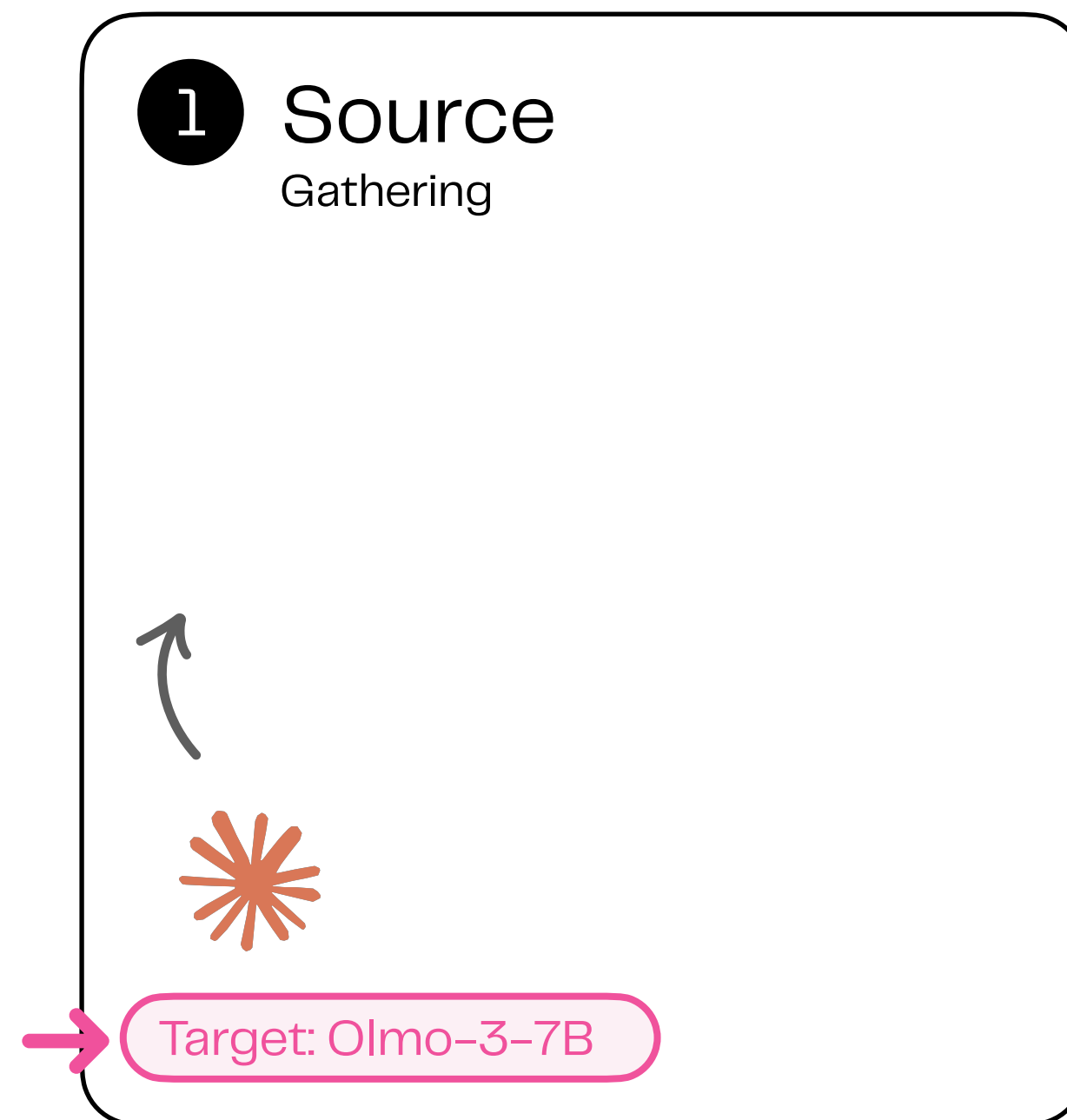
→ Target: Olmo-3-7B

Let's trace Olmo-3-7B with ModSleuth!

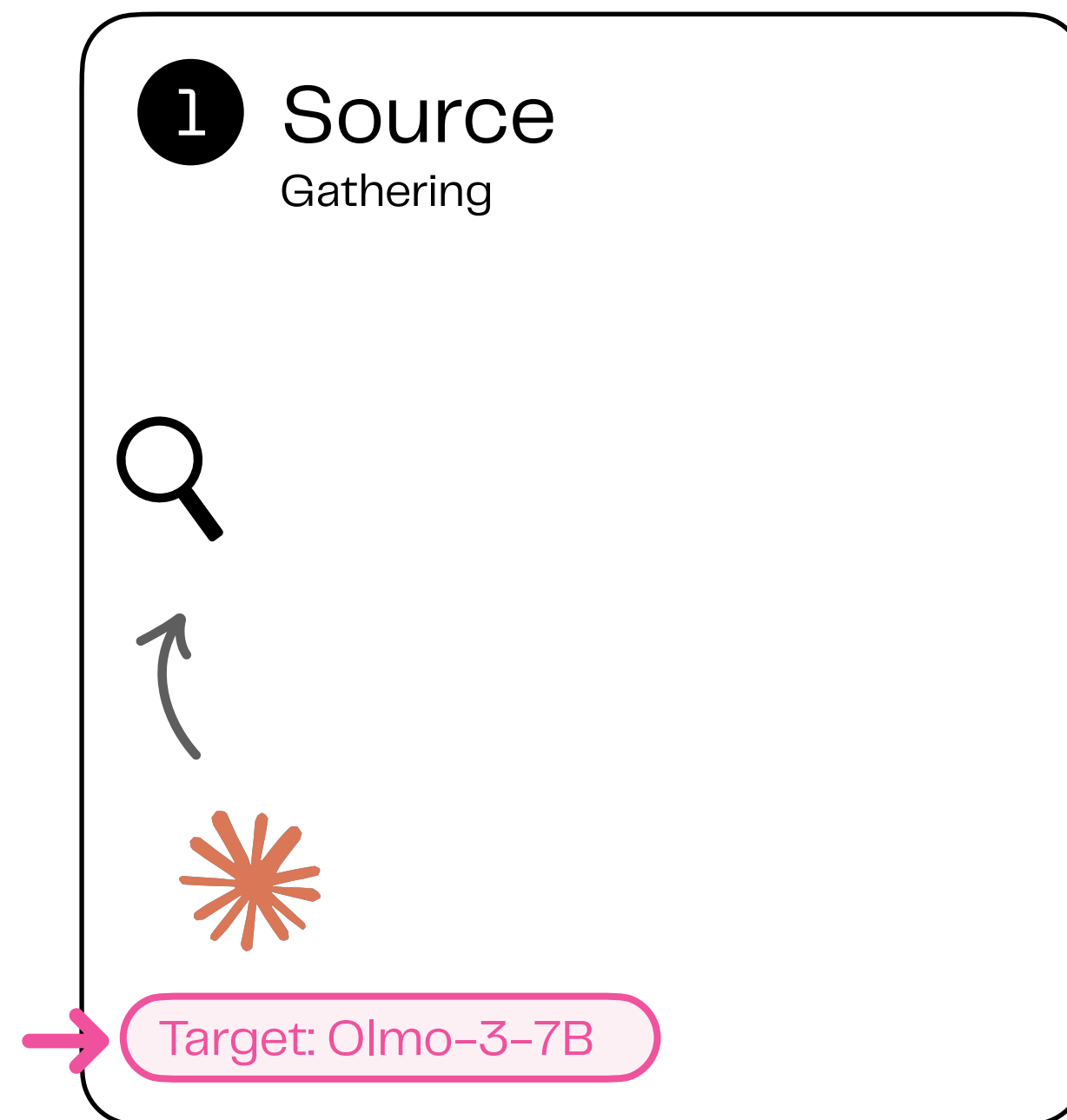
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1 Source Gathering



Target: Olmo-3-7B

Olmo 3

Olmo Team

Allyson Ettinger^{*1} Amanda Bertsch^{*1,3}
David Heineman^{*1} Dirk Groeneveld^{*1}
Hamish Ivison^{*1,2} Jacob Morrison^{*1,2}
Matt Jordan^{*1} Mayee Chen^{*1,4} Micha
Pete Walsh^{*1} Pradeep Dasigi^{*1} Robe
Scott Geng^{*1,2} Shane Arora^{*1} Shasha
Tyler Murray^{*1} Tyler Romero^{*1} Victori

Akari Asai^{1,2} Akshita Bhagia¹ Alexande
Chloe Anastasiades¹ Costa Huang¹ D
Jaron Lochner¹ Jiacheng Liu¹ Lester Ji
Michael Schmitz¹ Michael Querquin¹ Mi
Rui Xin² Rulin Shao² Sam Skjonsberg¹
Tucker Wilde¹ Valentina Pyatkin¹ Will

allenai **OLMo-3-7B-Instruct**

Text Generation Transformers Safety

Model card Files and versions Text

Model Details

Model Card for OLMo 3 7B Instruct

Model Card for OLMo 3 7B Instruct

Model Card for OLMo 3 7B Instruct

Model Card for OLMo 3 7B Instruct

Model Card for OLMo 3 7B Instruct

Model Card for OLMo 3 7B Instruct

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allenai **OLmo-3-7B-Instruct**

Text Generation Transformers Safety

Model card Files and versions test

Model Details



Model Card for Olmo 3 7B Instruct

OLMo-core Public

main 316 Branches

finbartimbers Use case: Instruct

claude/llm/training-smoke-test

github

docs

src

.gitignore

.readthedocs.yaml

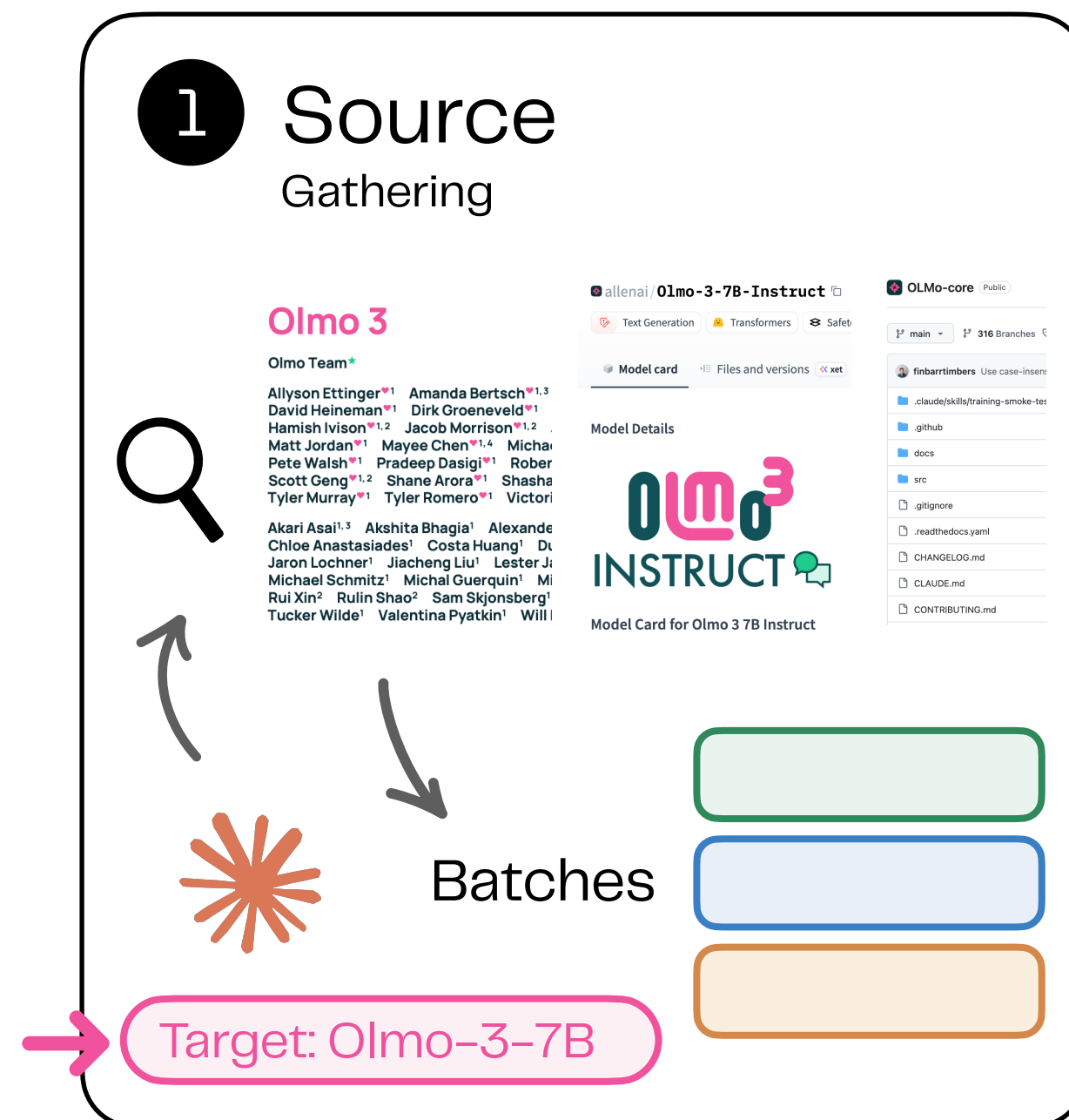
CHANGELOG.md

CLAUDE.md

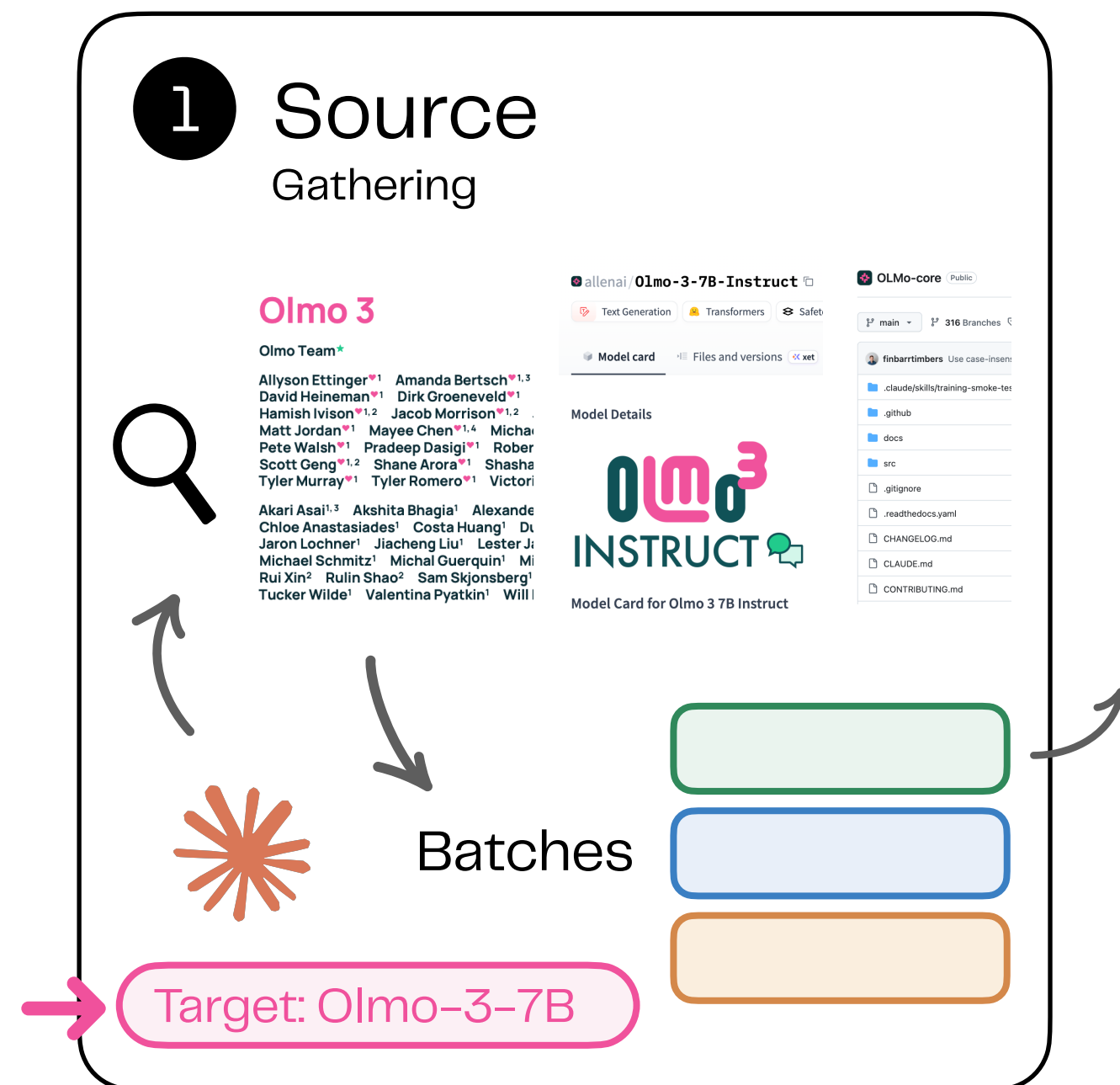
CONTRIBUTING.md

Target: Olmo-3-7B

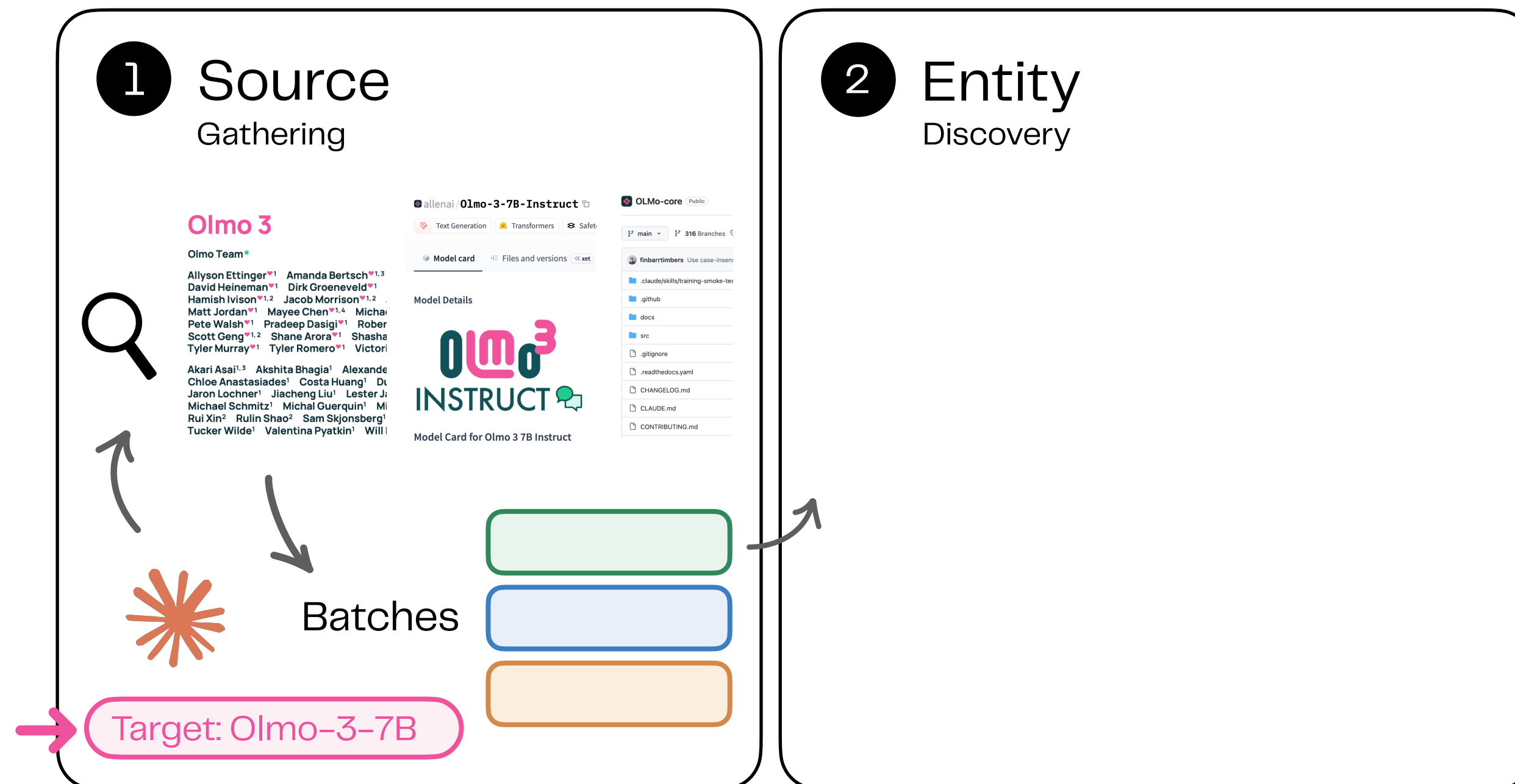
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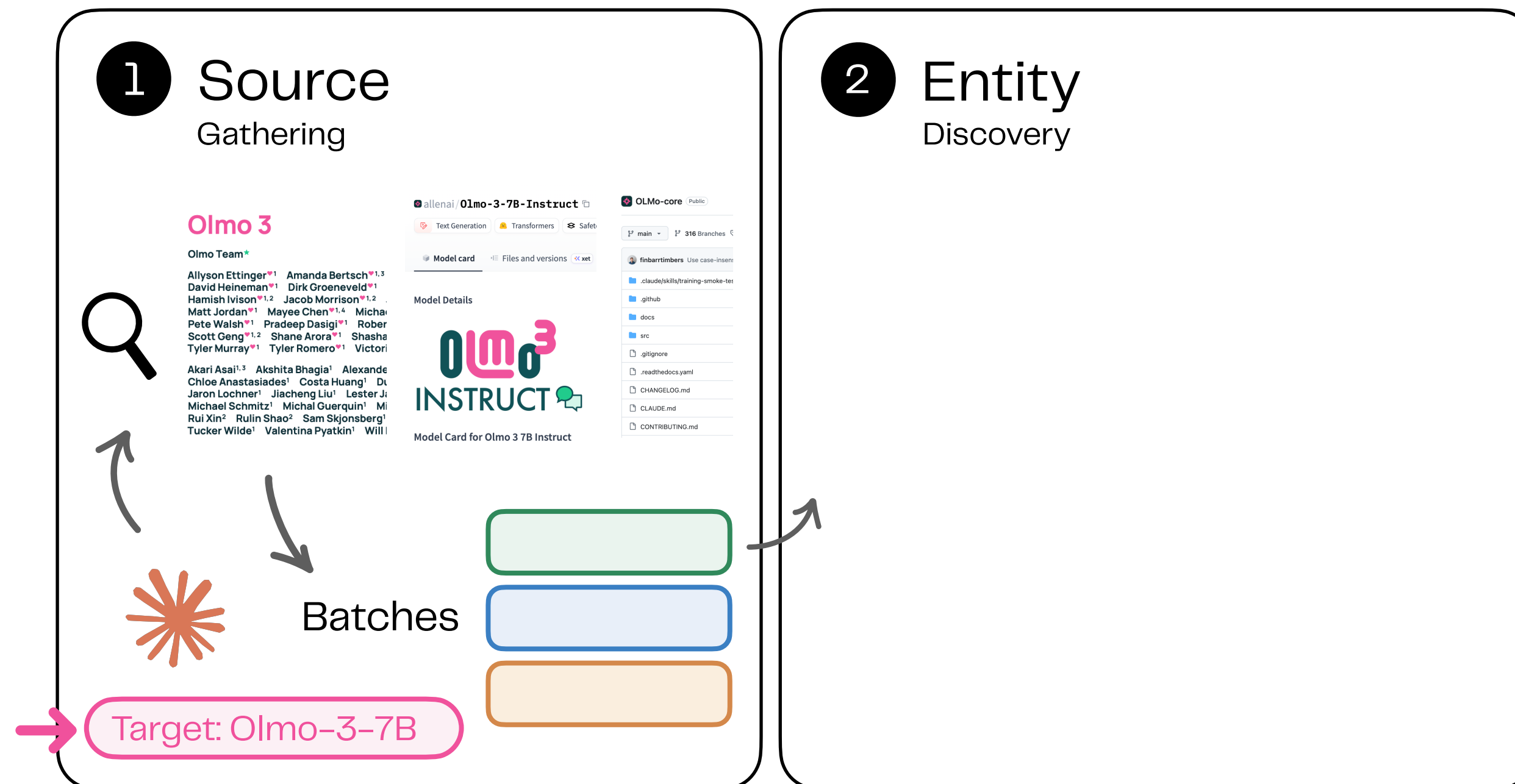
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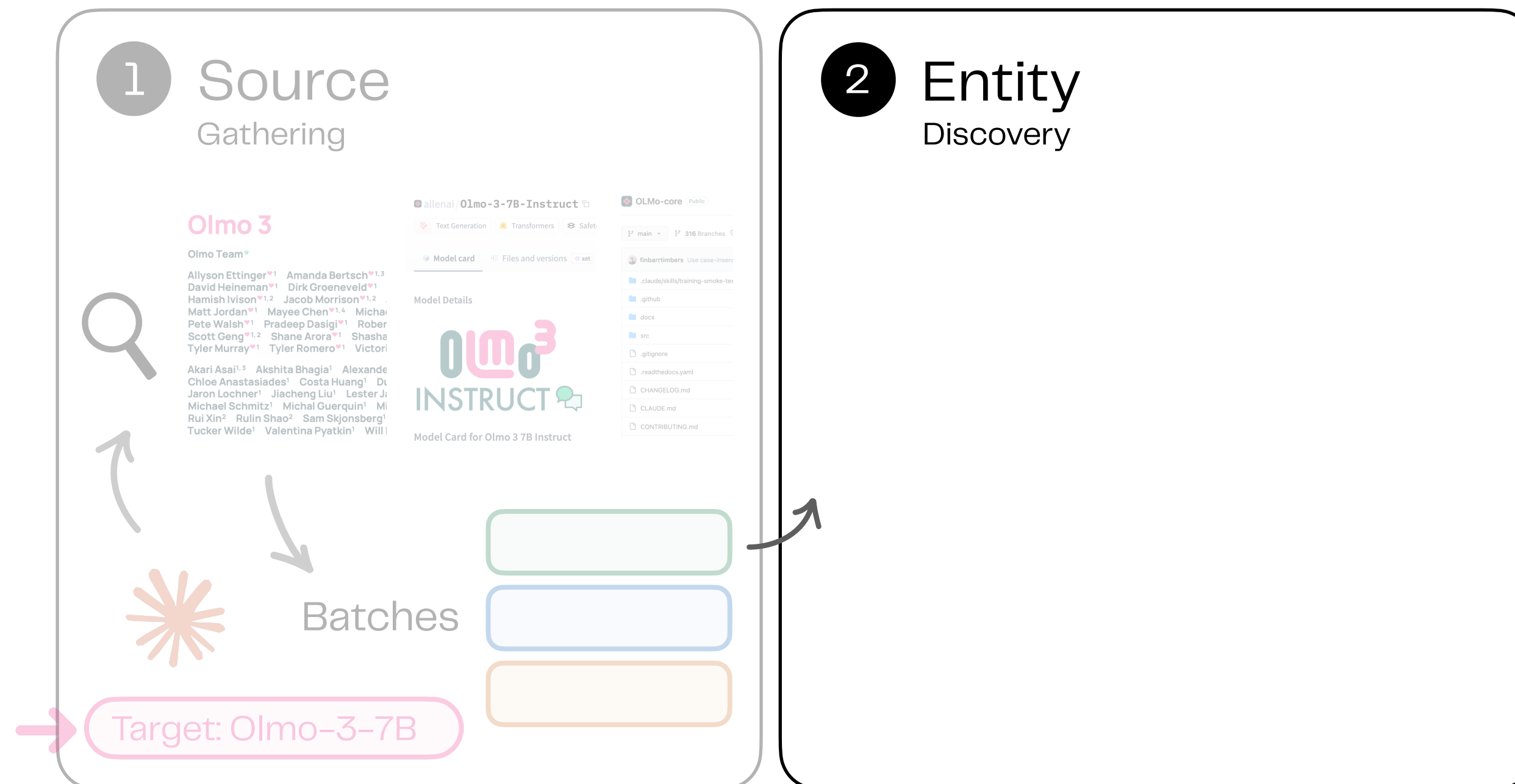
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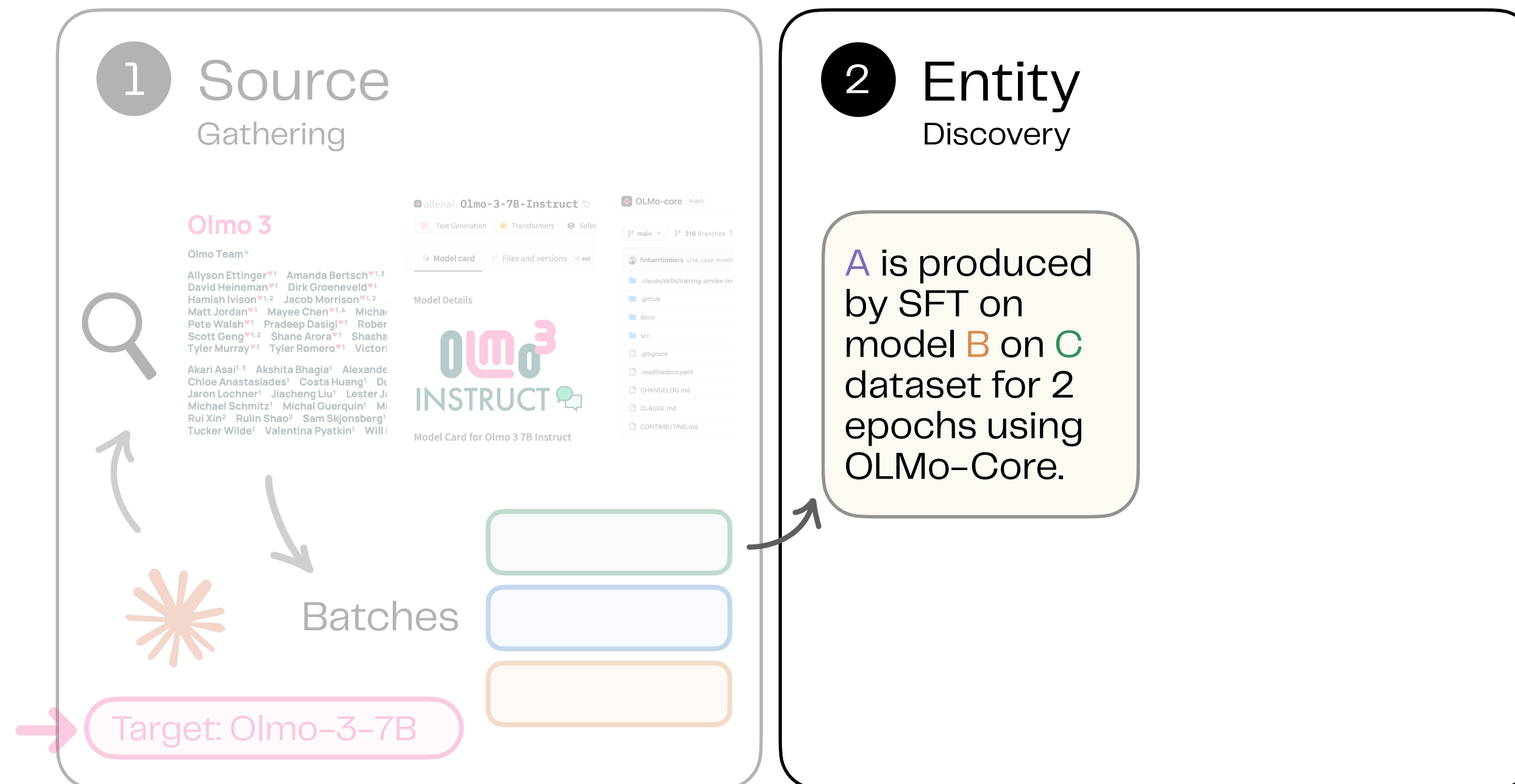
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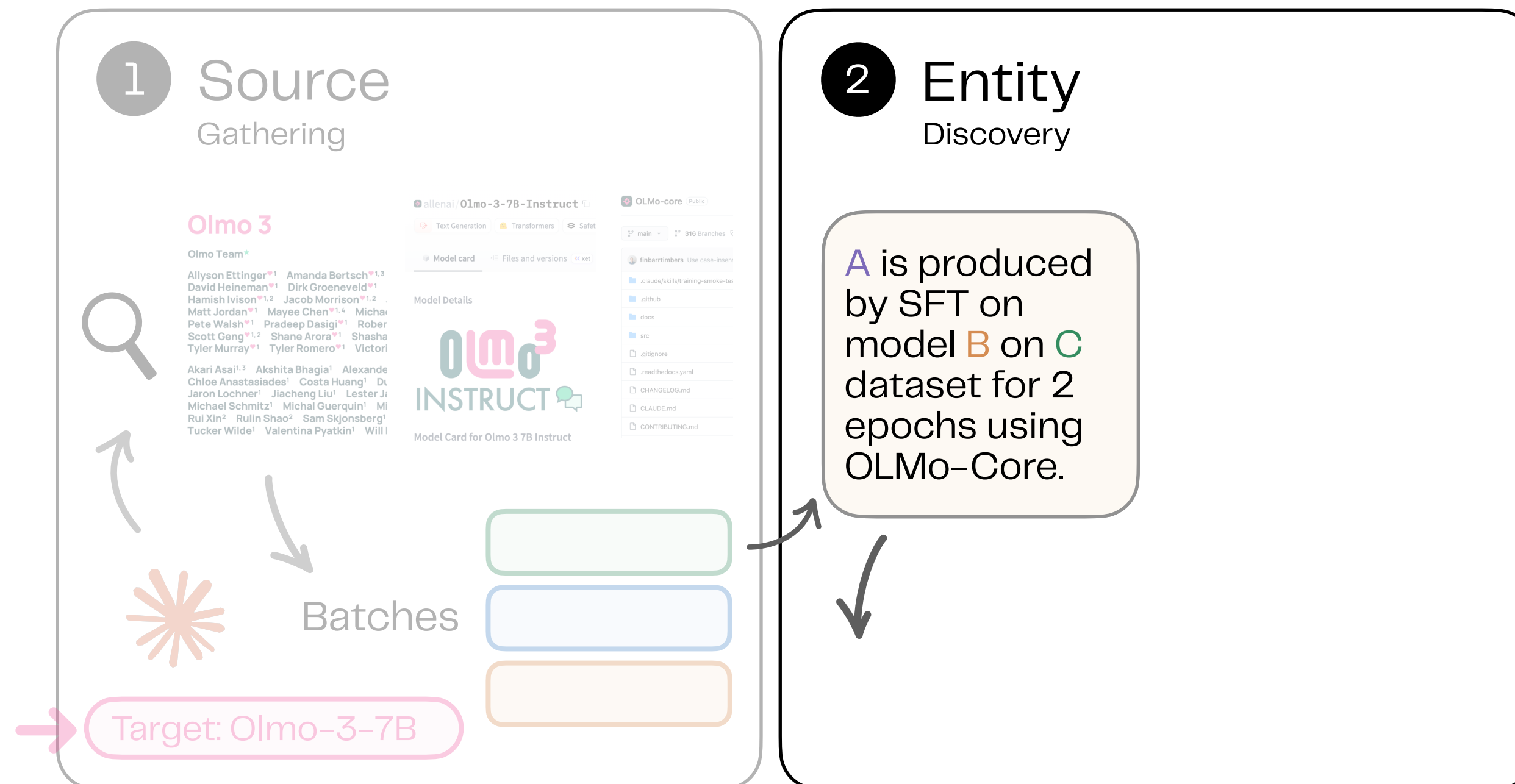
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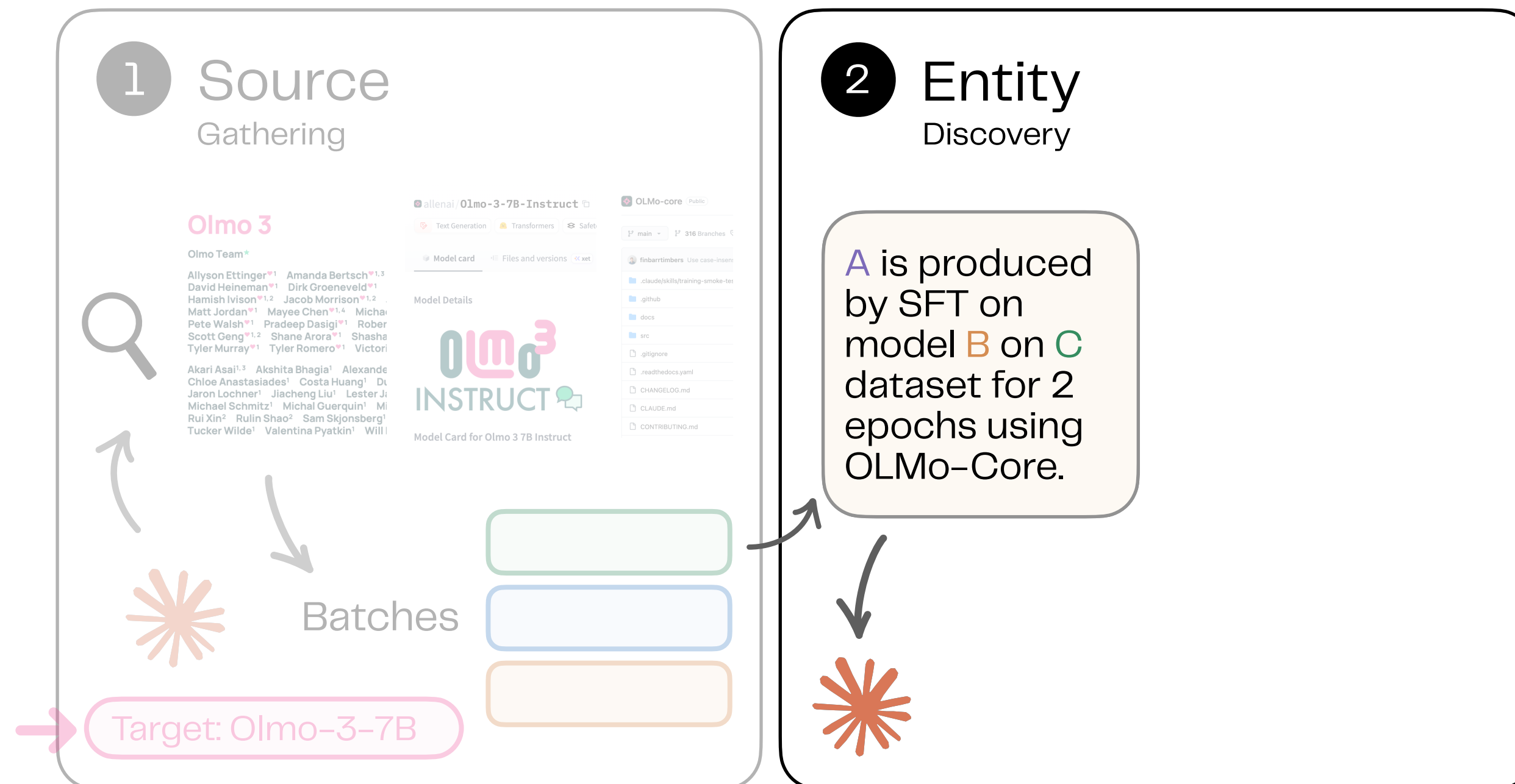
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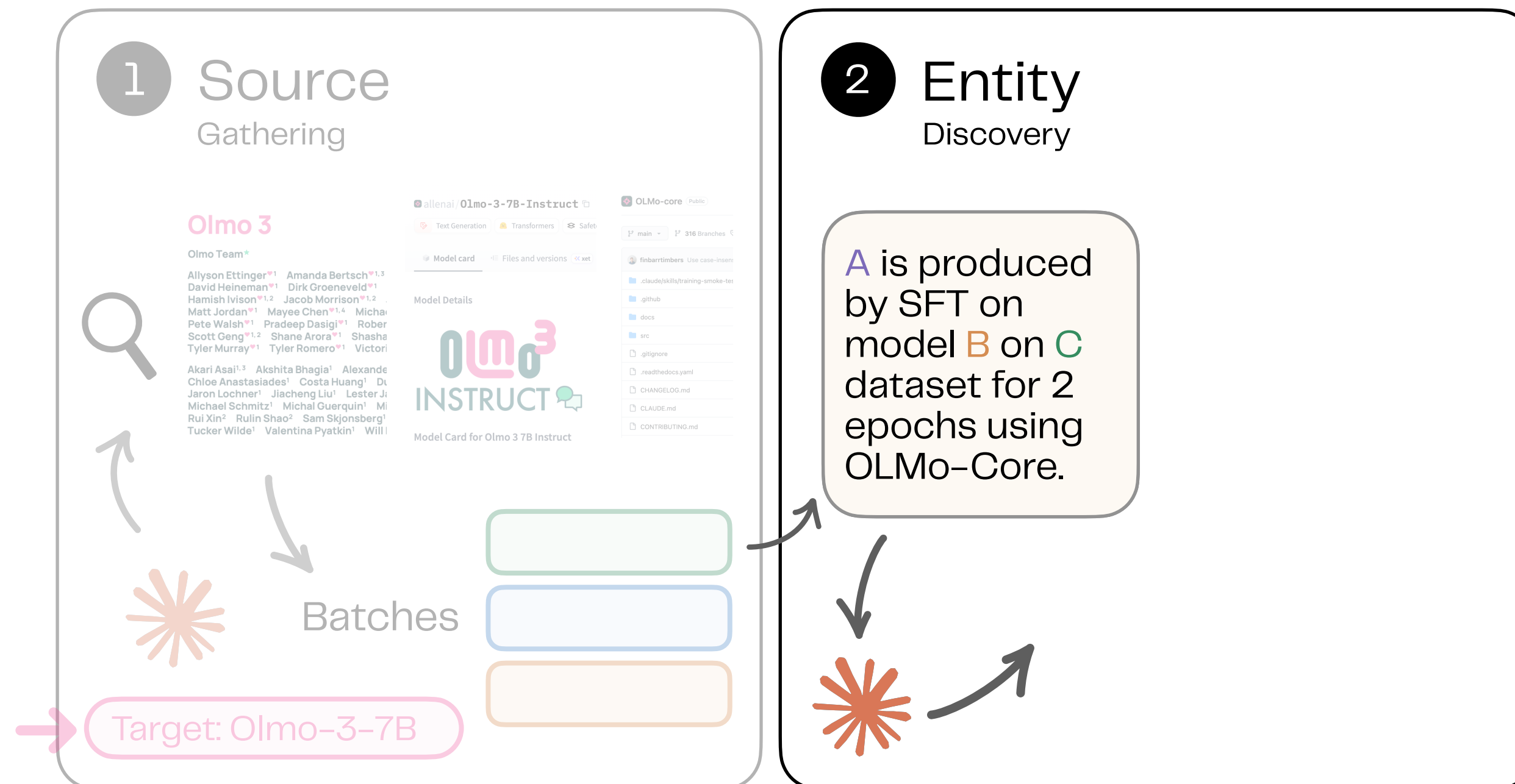
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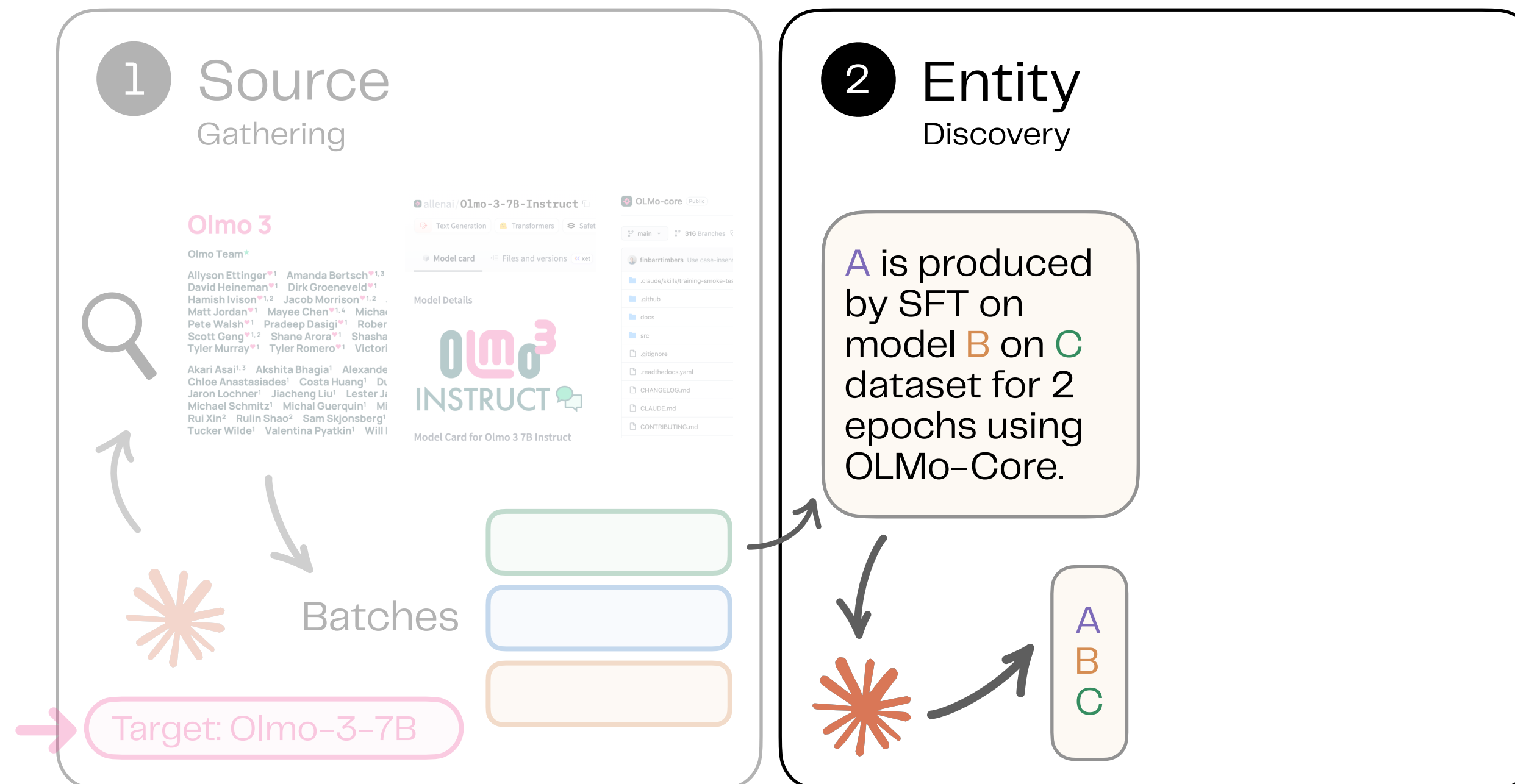
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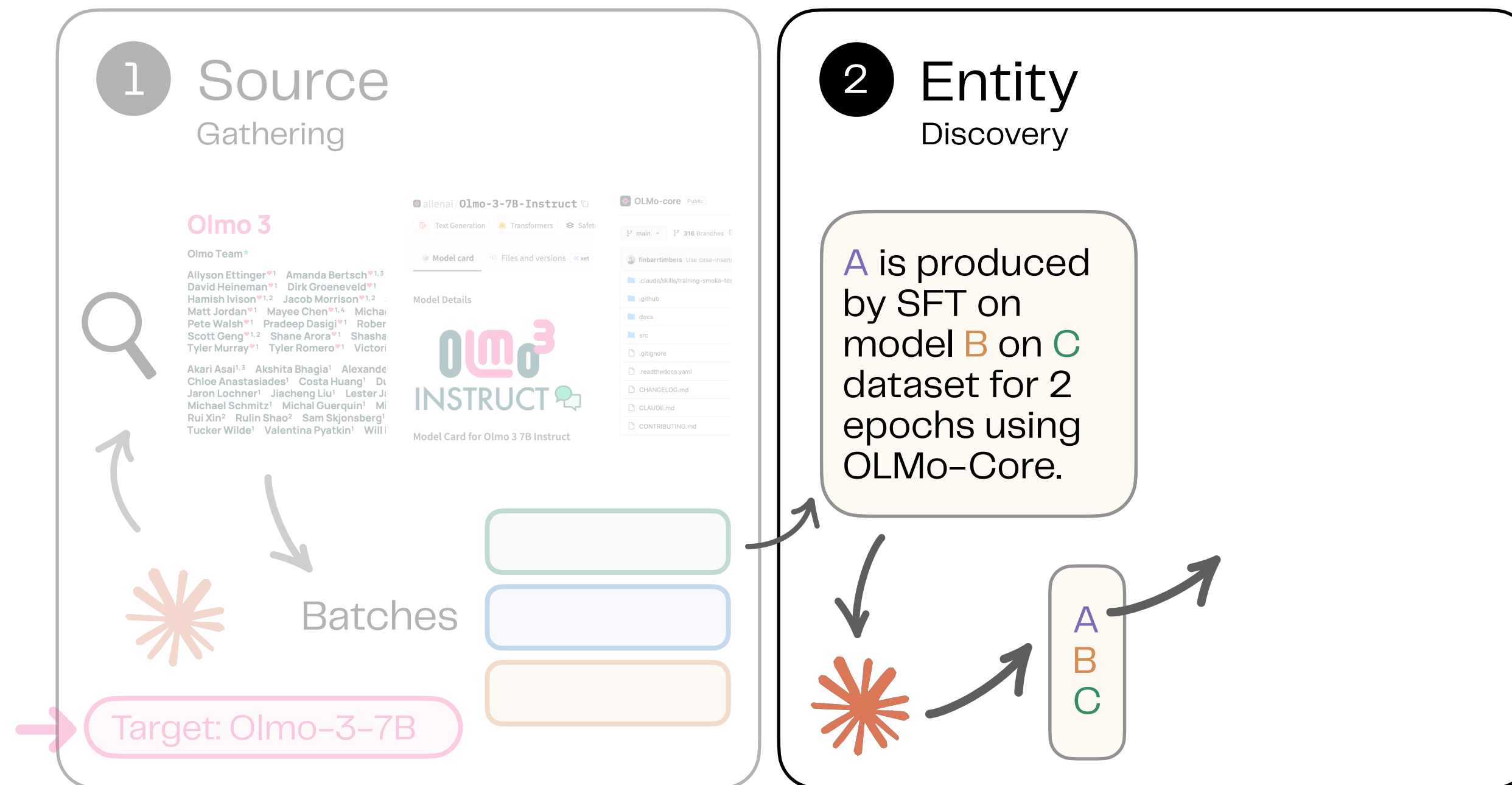
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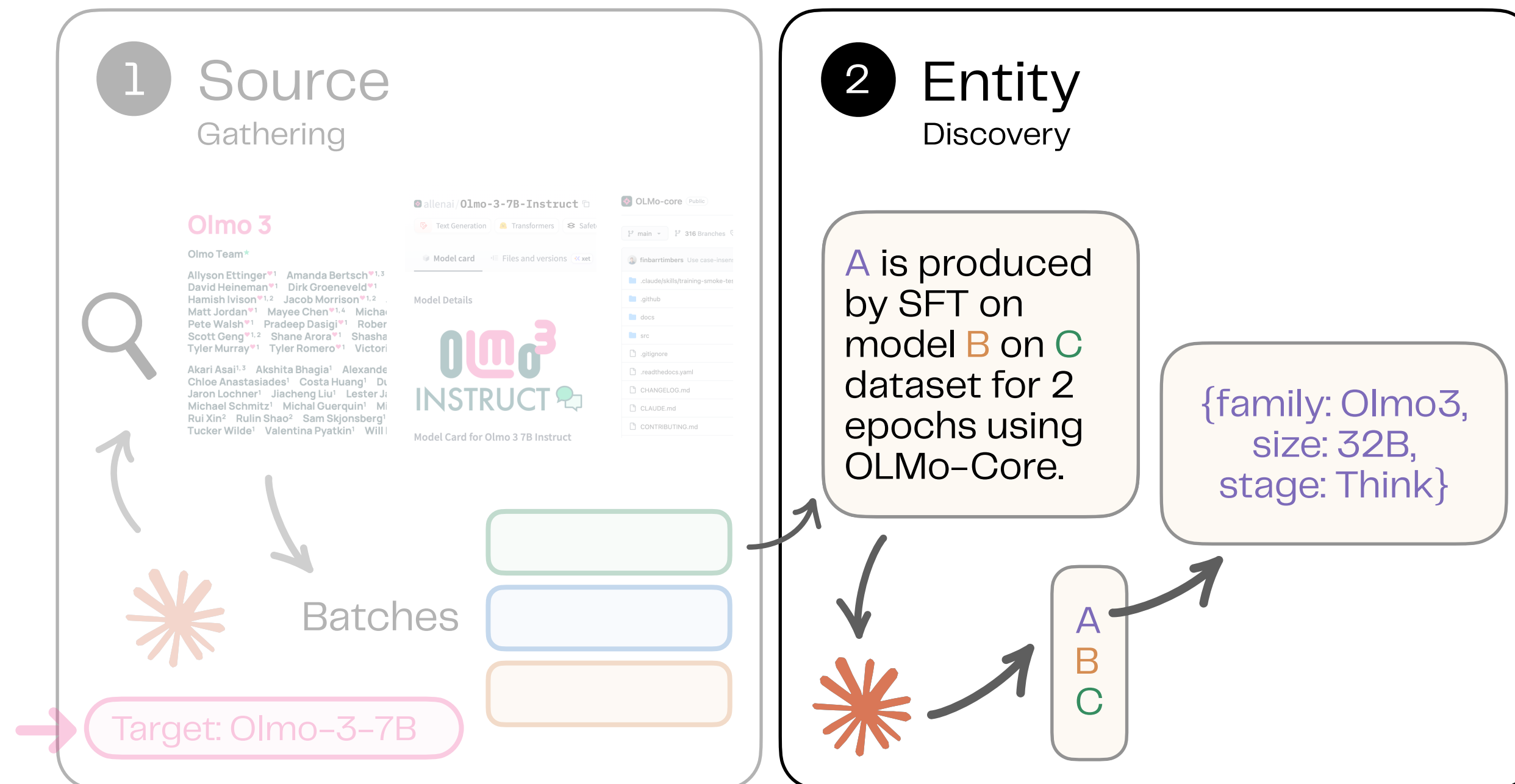
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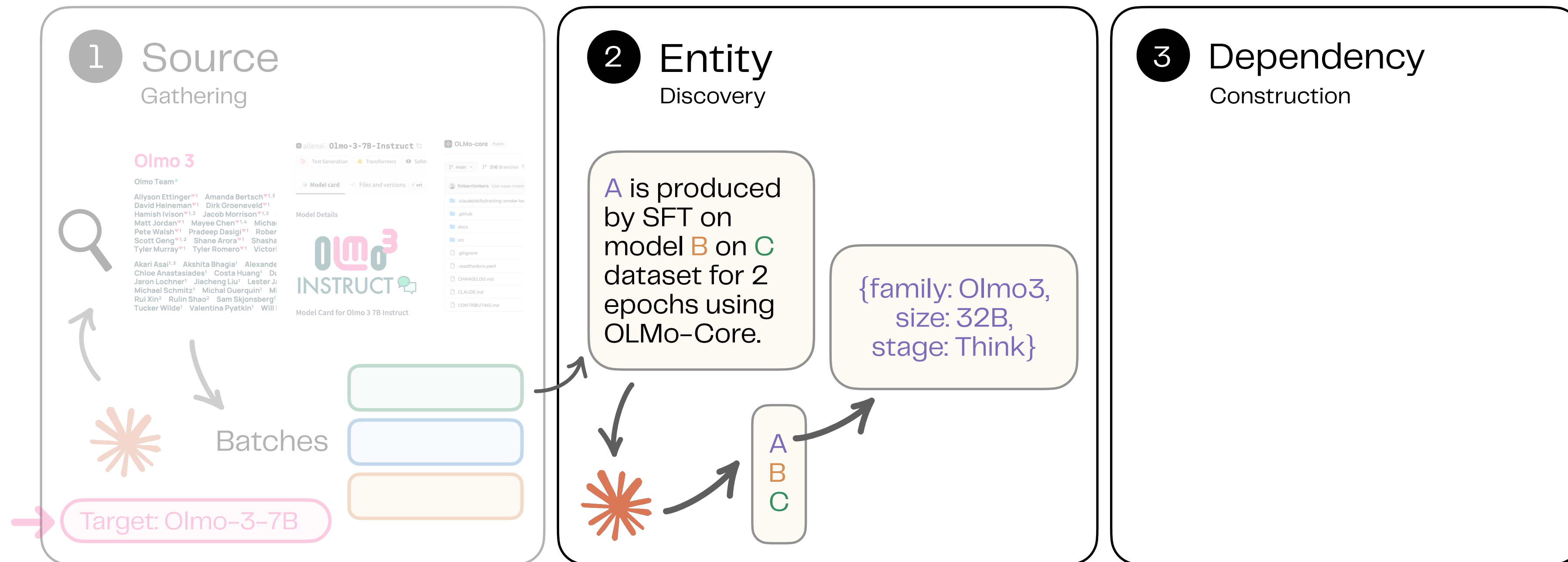
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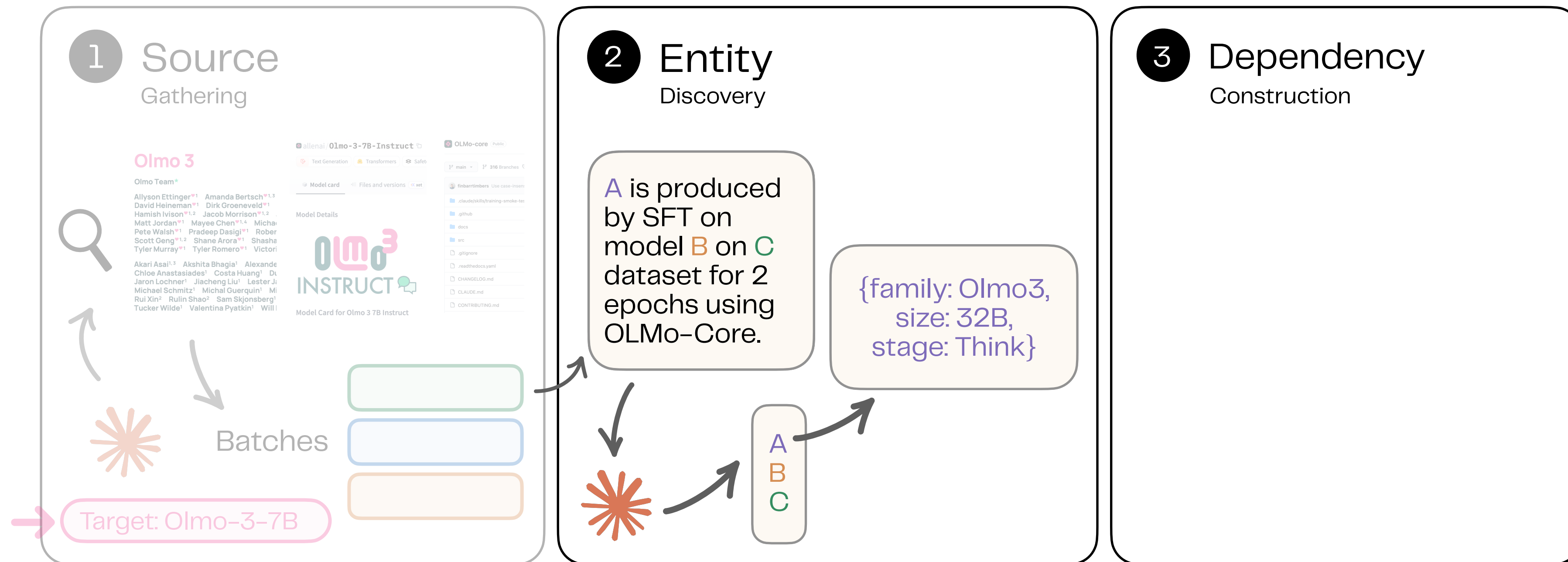
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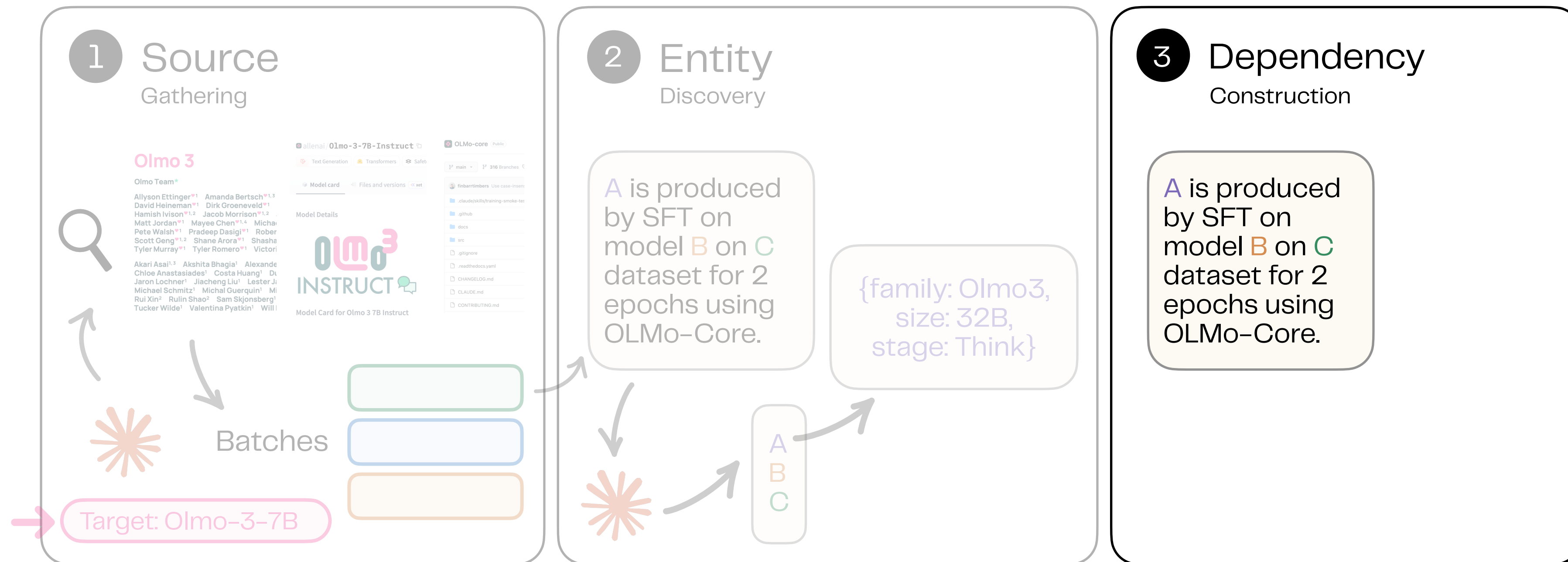
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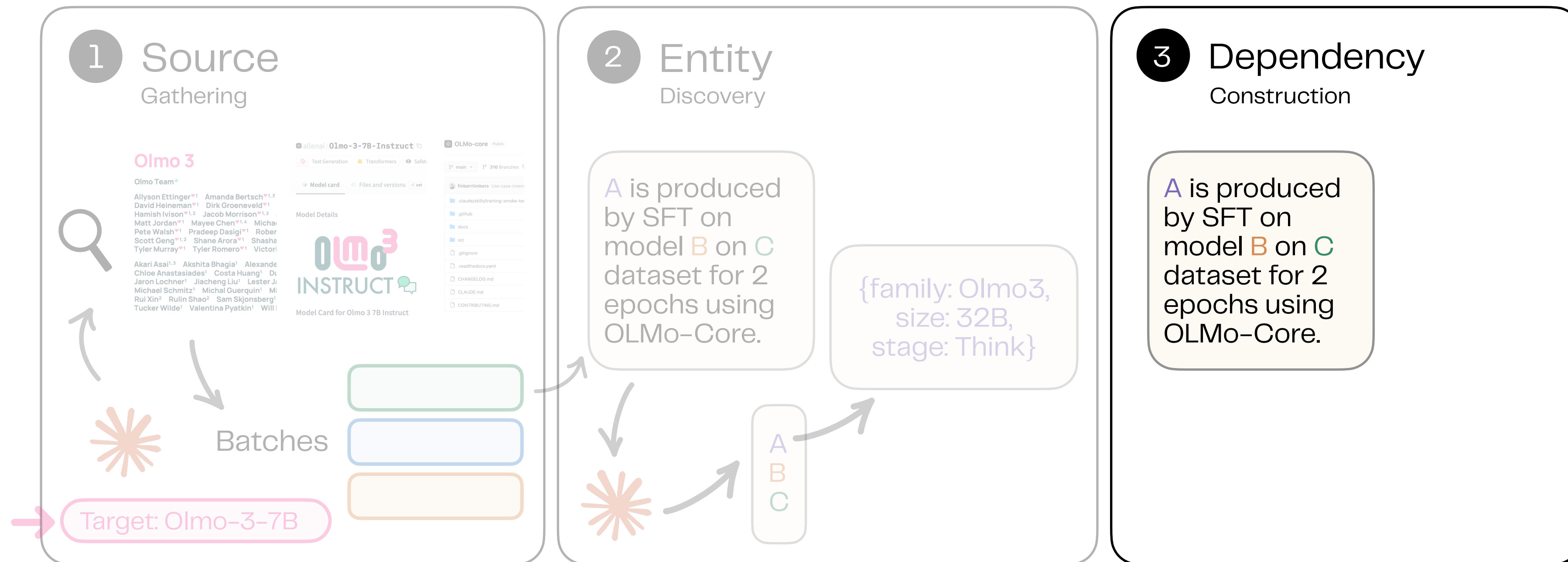
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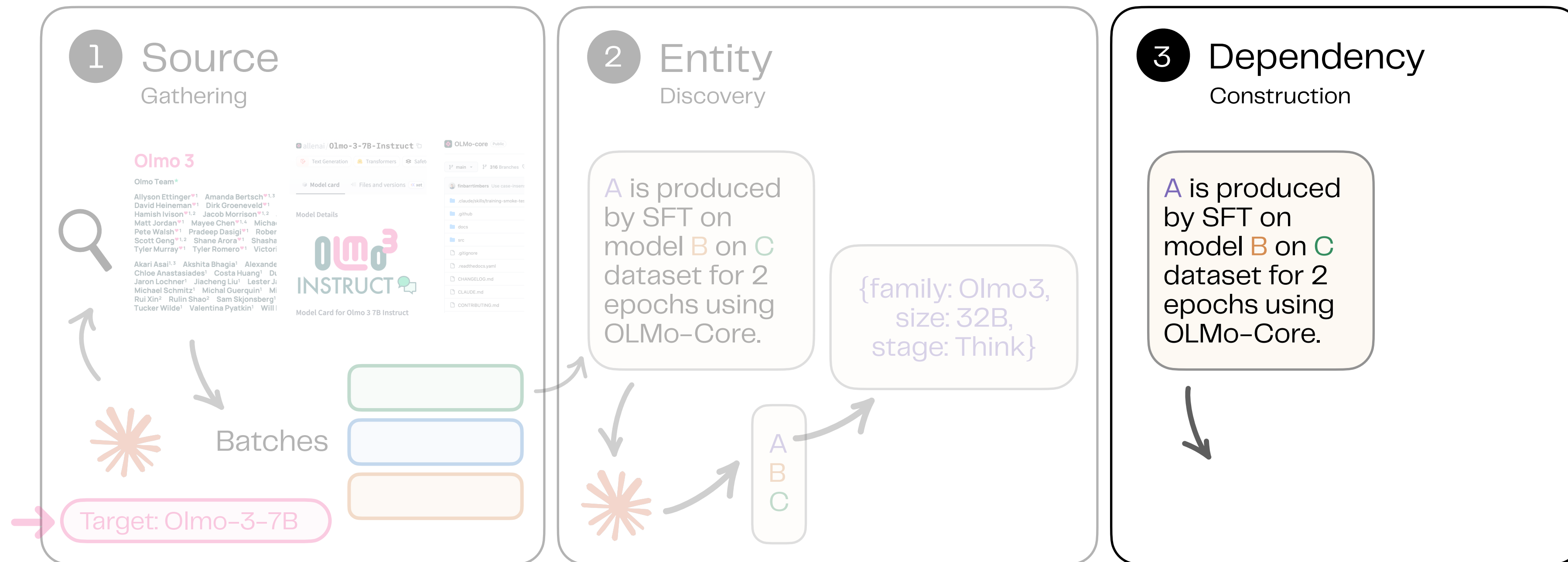
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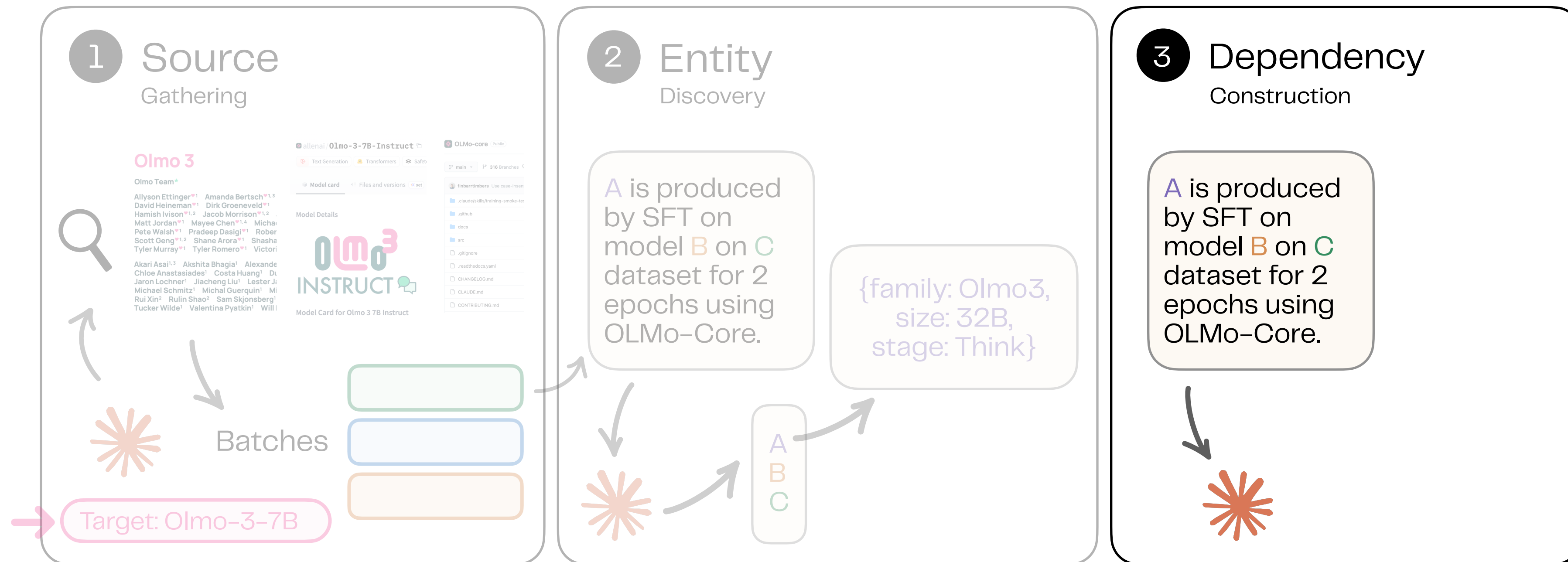
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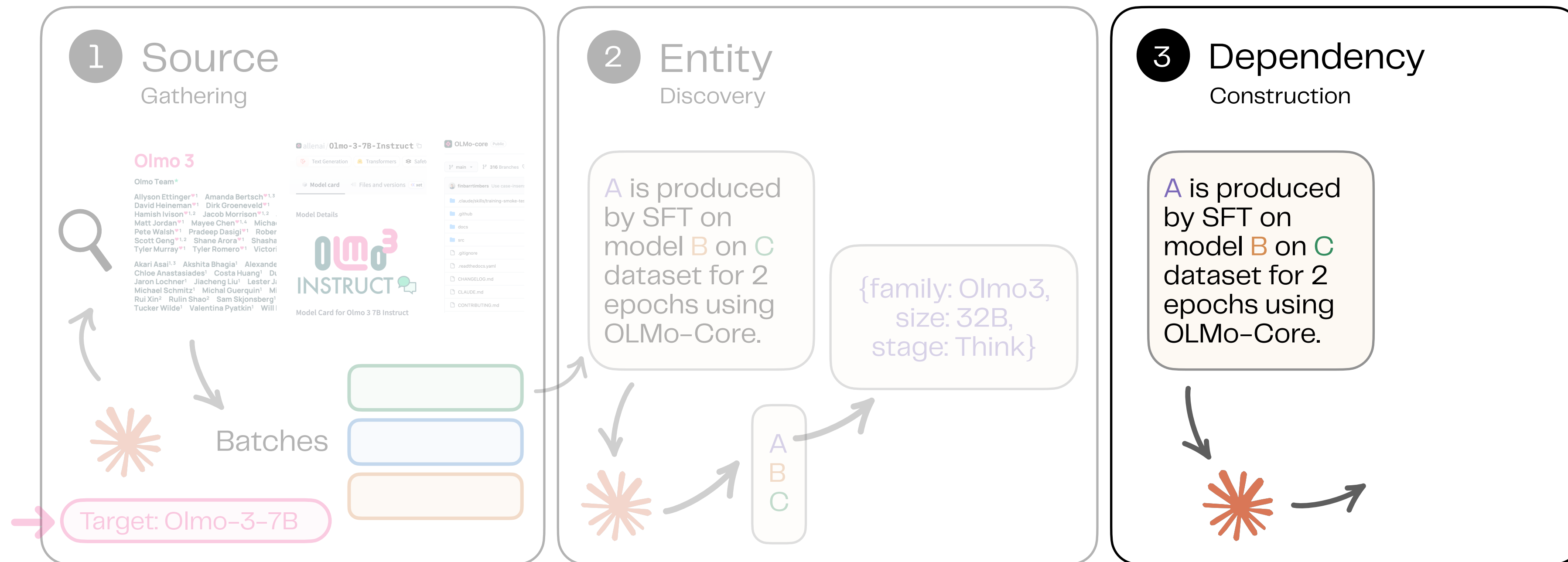
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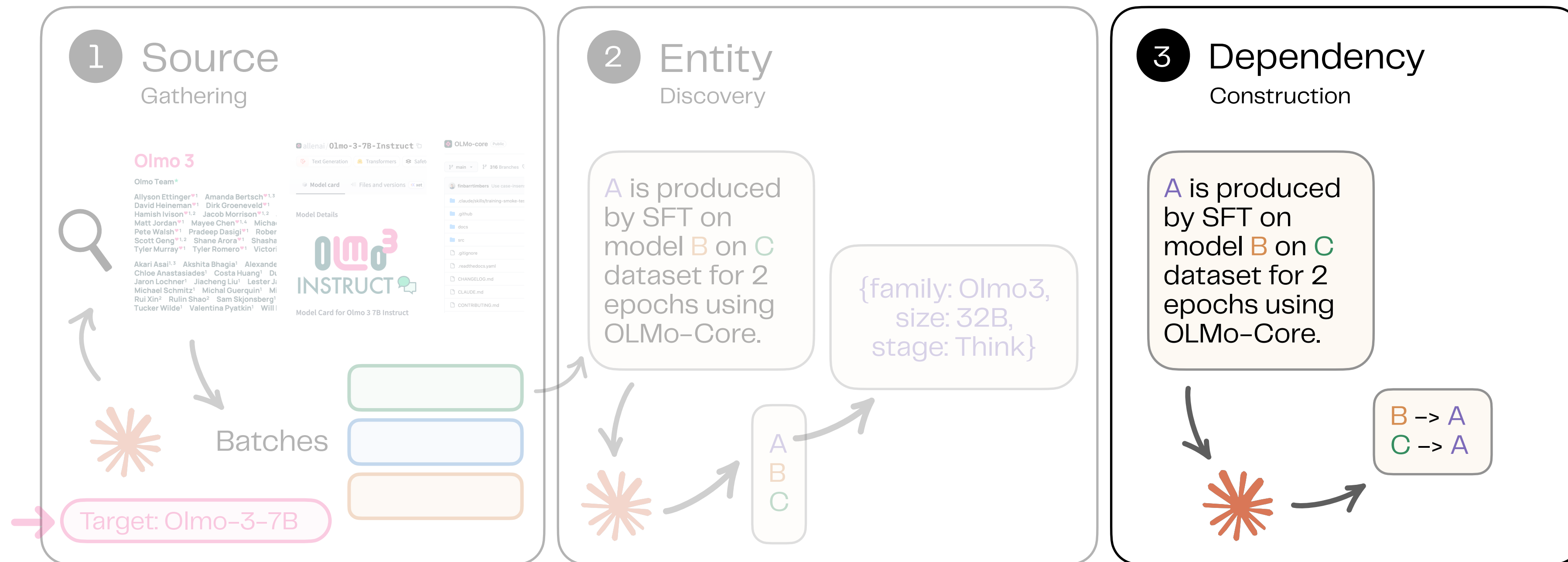
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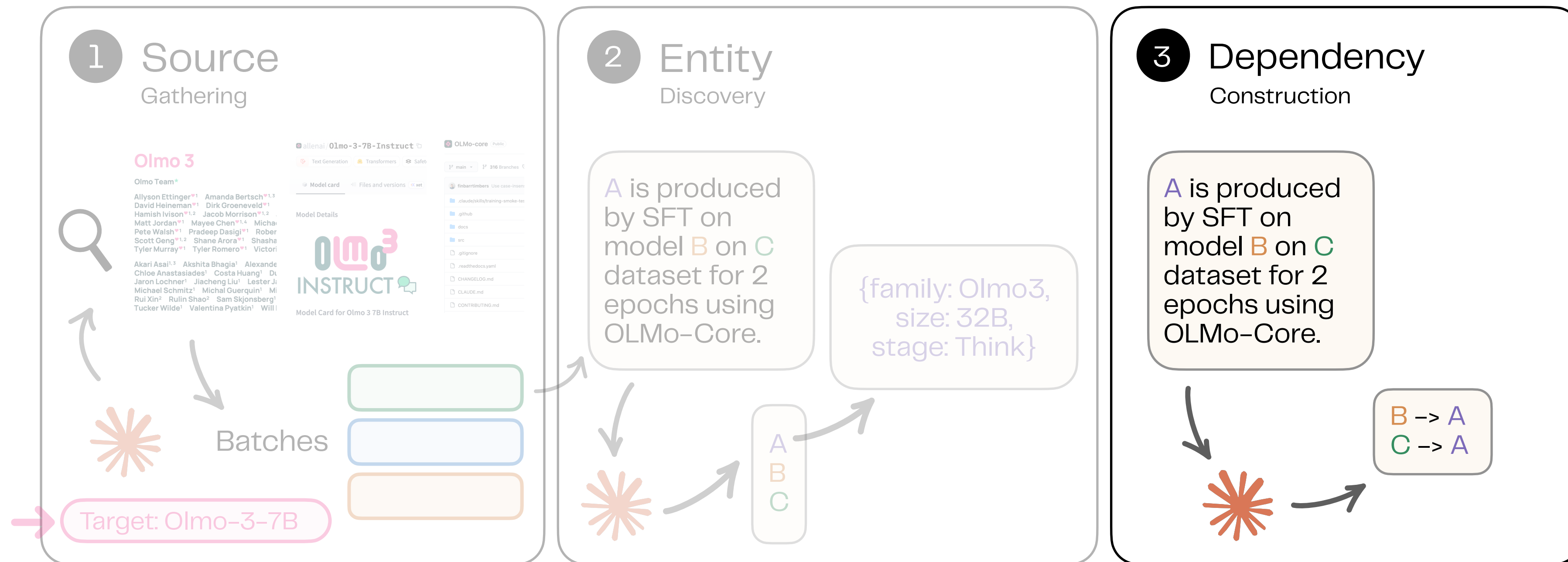
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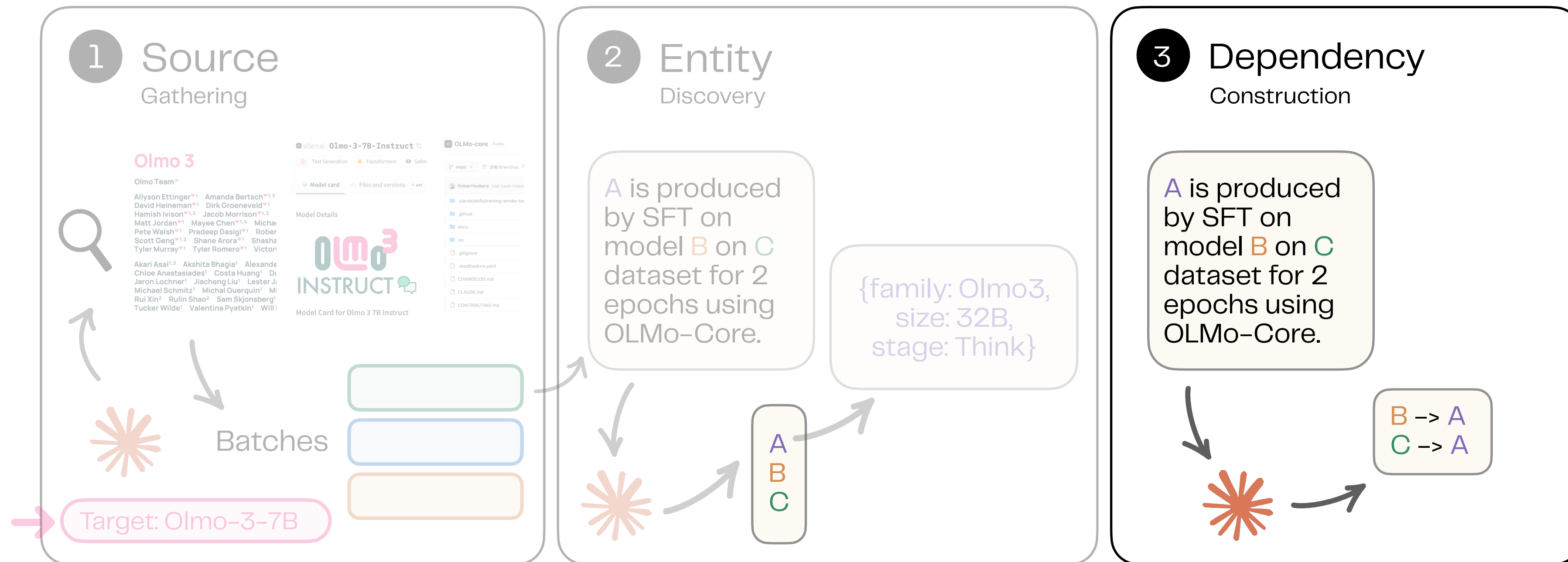
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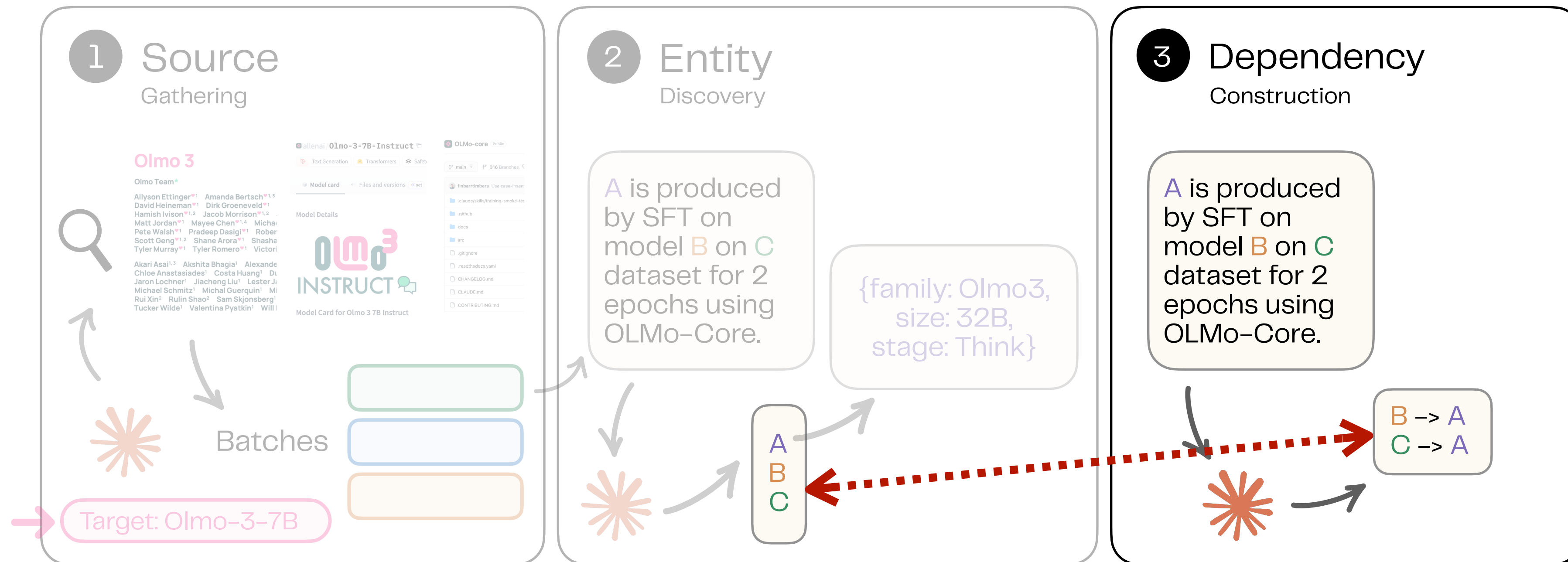
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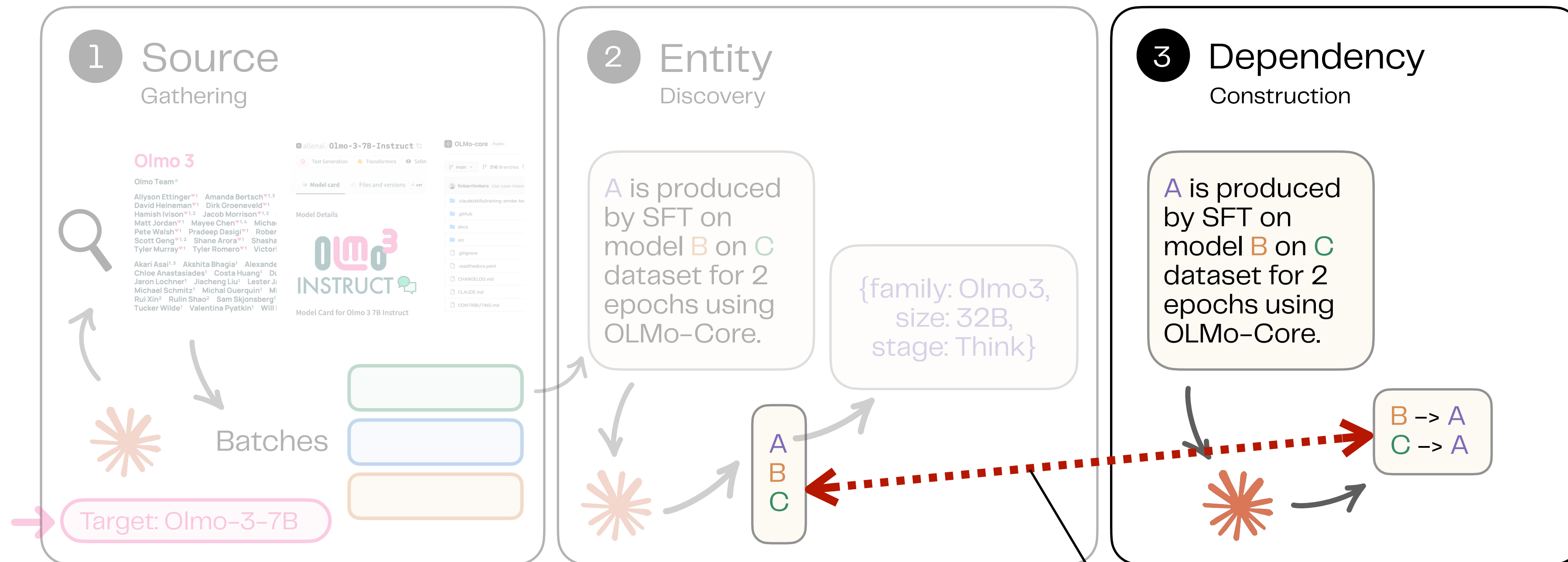
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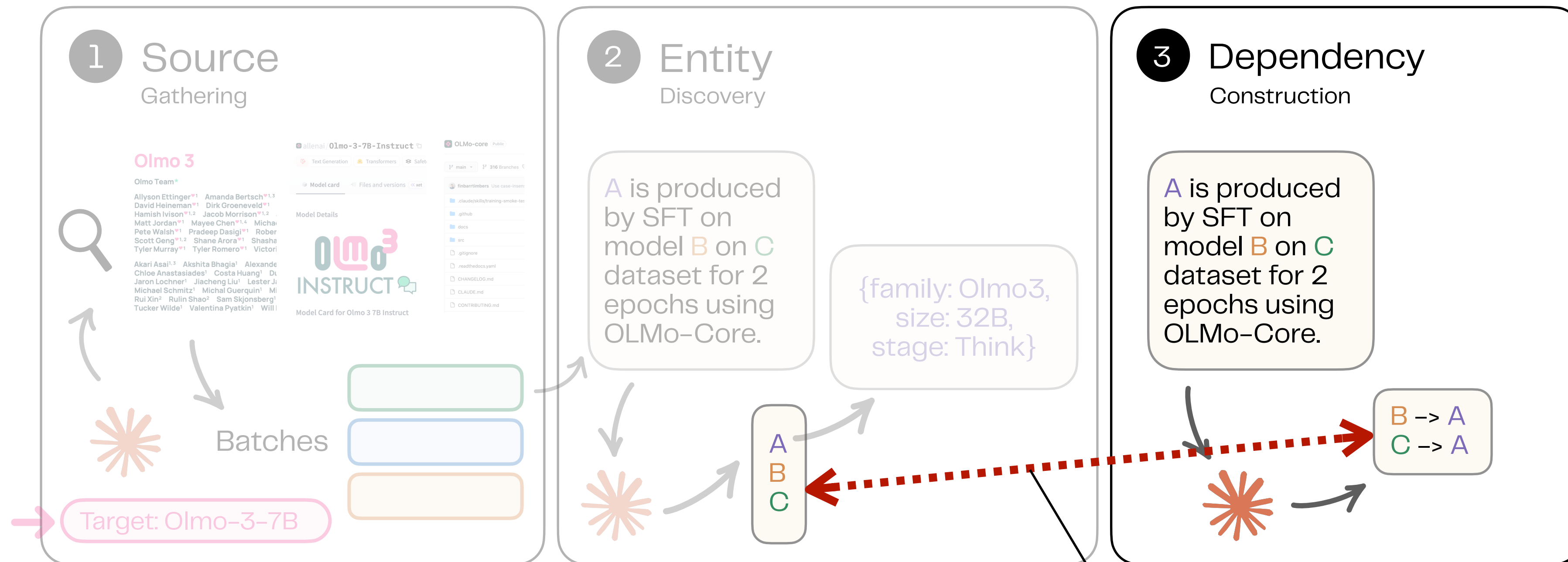


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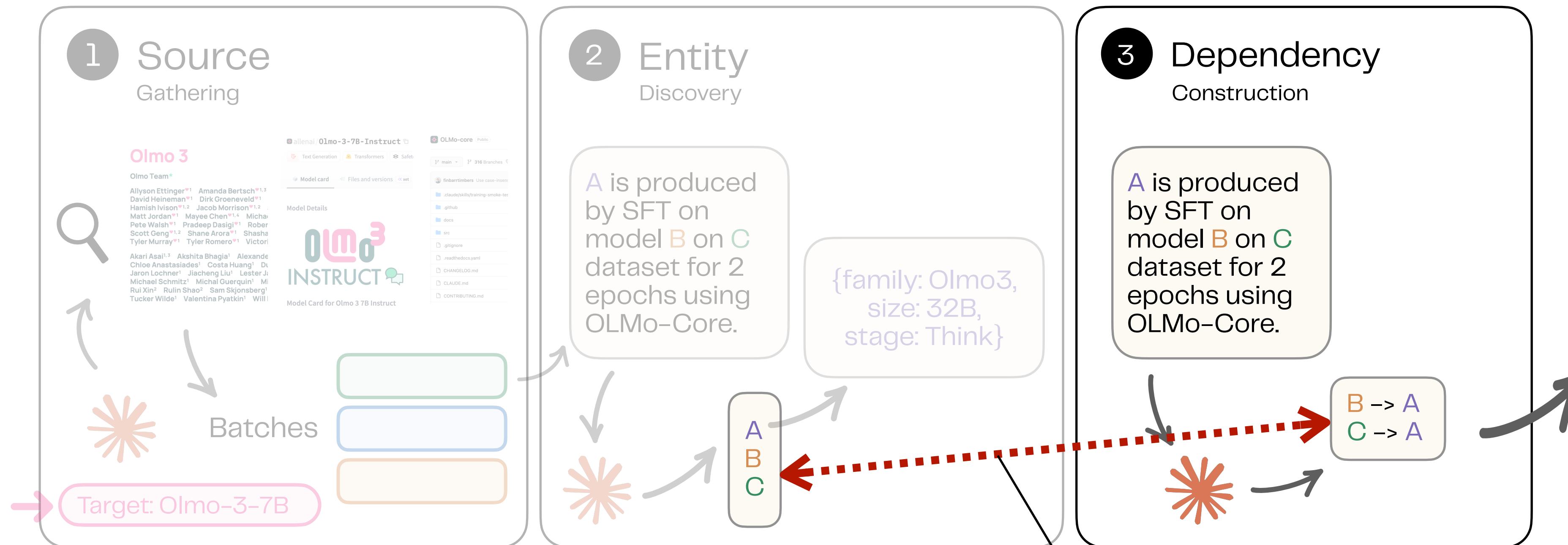
Recall that we have already identified the nodes in the graph; all that remains is to connect them

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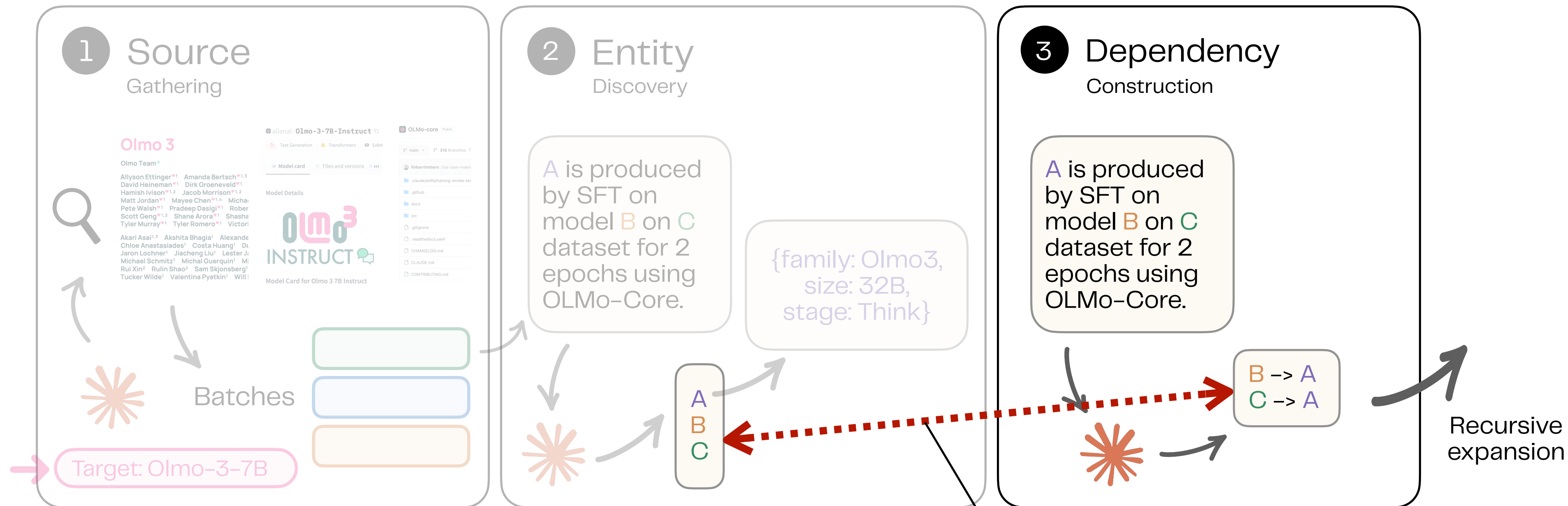
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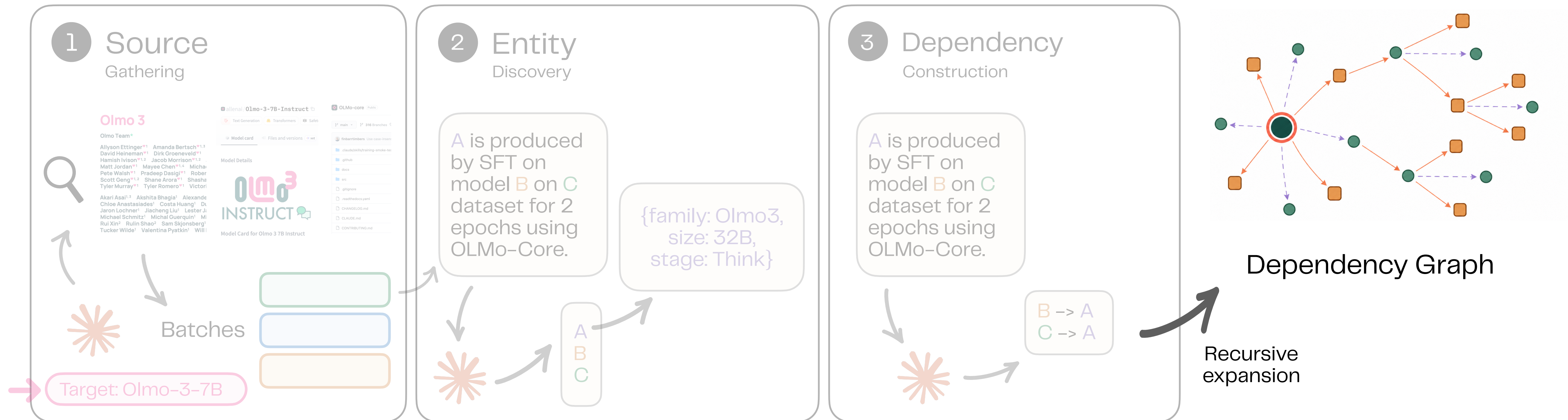
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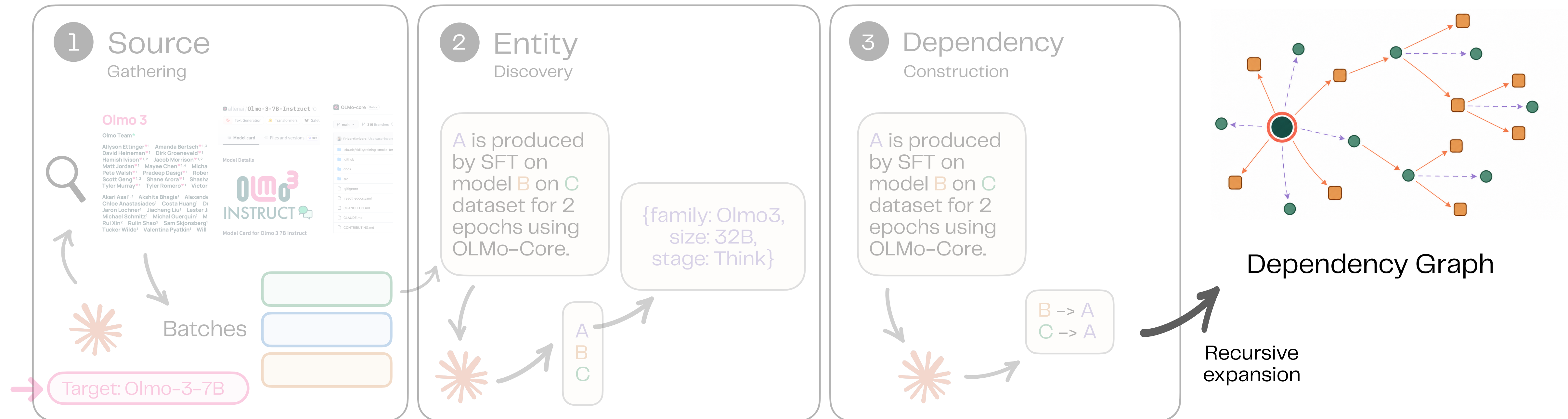


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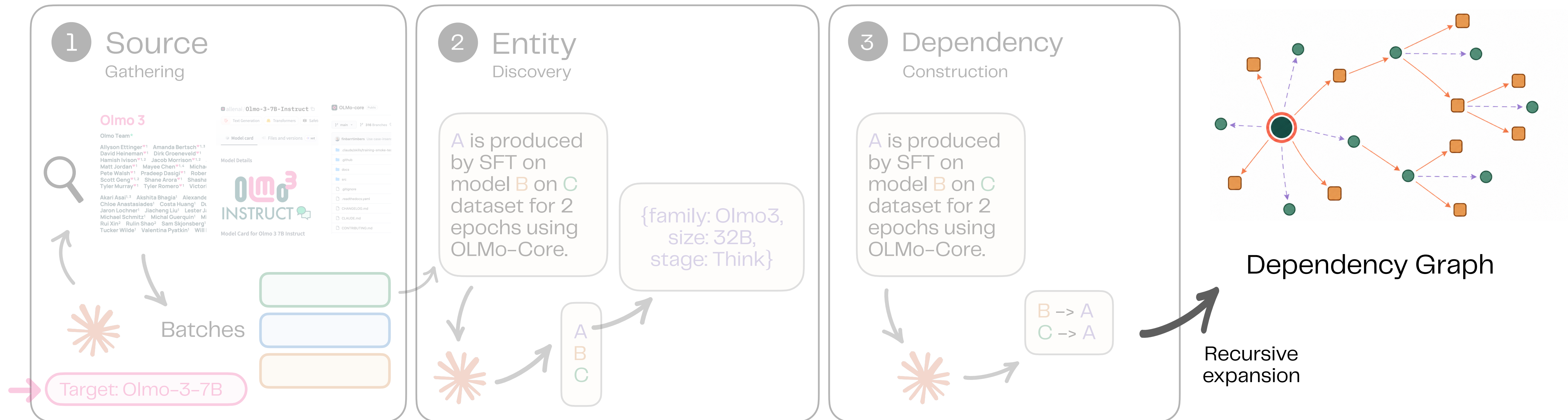
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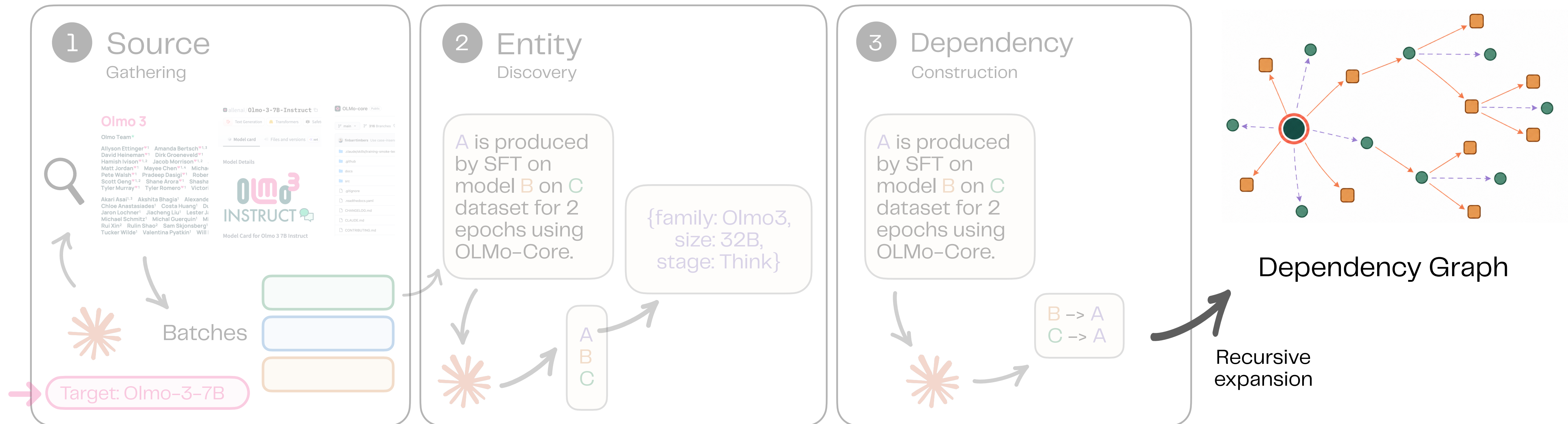
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Design of ModSleuth

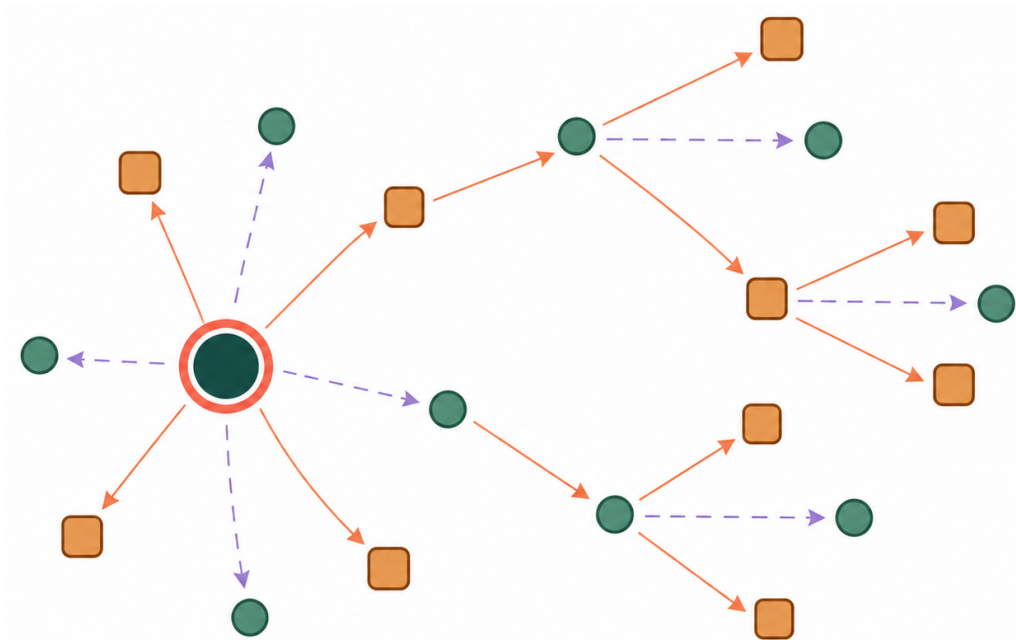


Design of ModSleuth

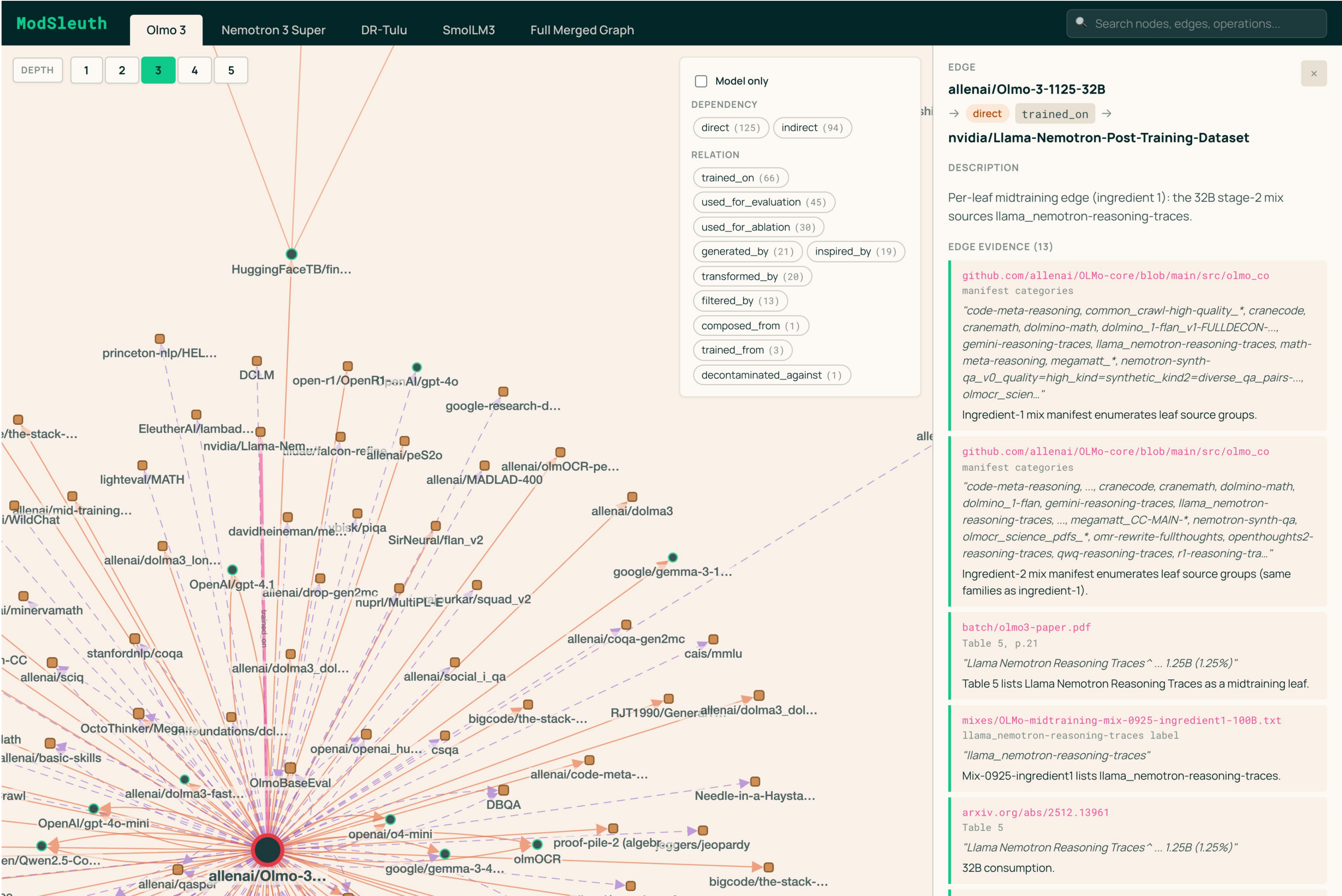


After having the **original graph** from our system, we use Claude Sonnet to audit every edge and **only keep and release the *verified* edges**. (We also experimented the agreement w/ other verifiers.)

Output of ModSleuth

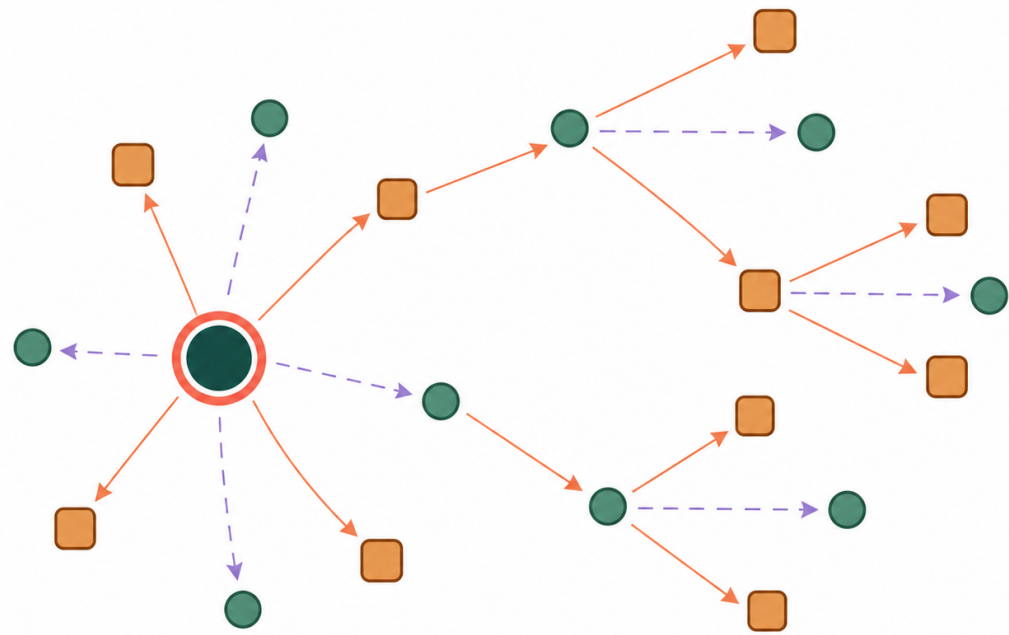


Dependency Graph
(All verified)

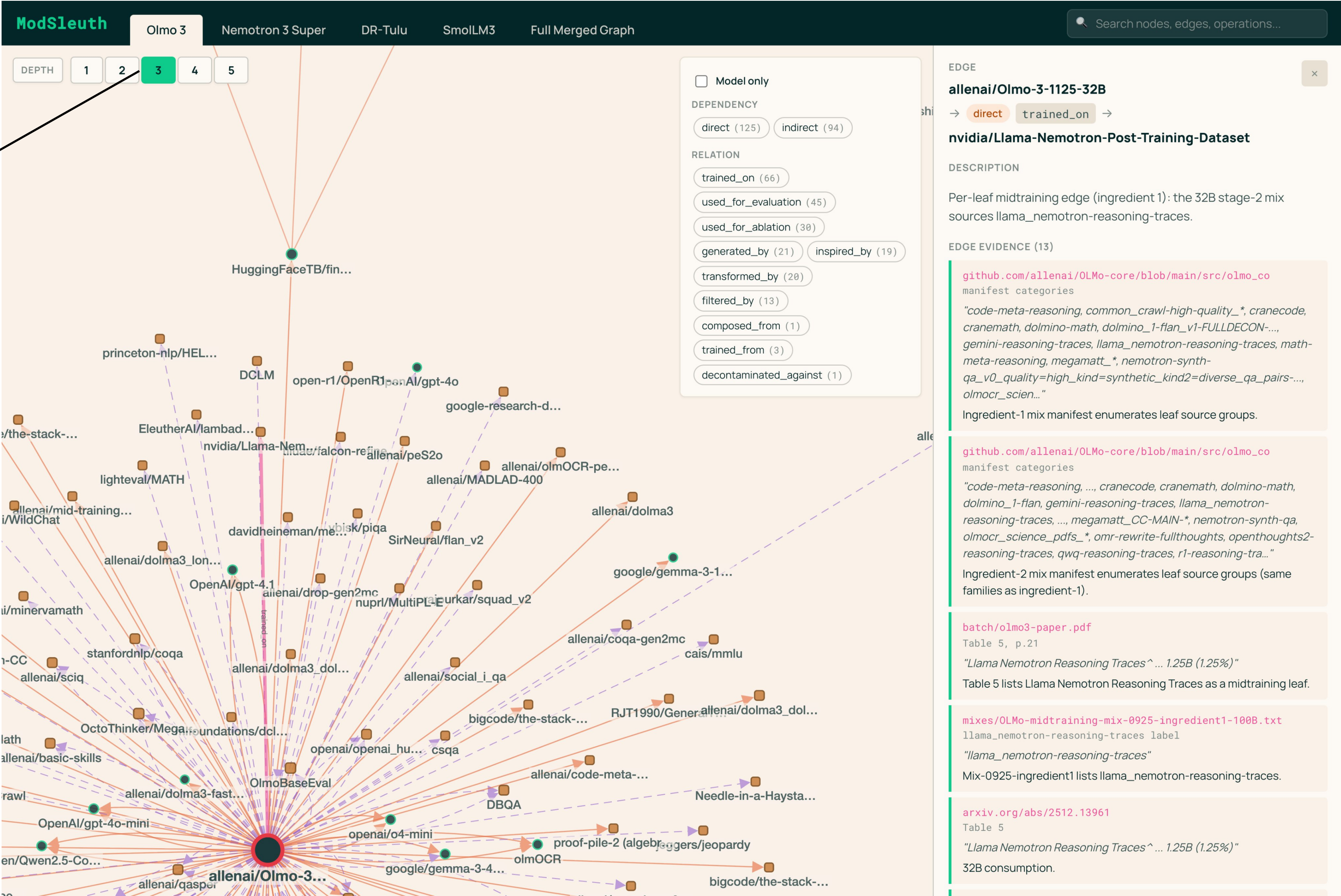


Output of ModSleuth

Recursive Exploration



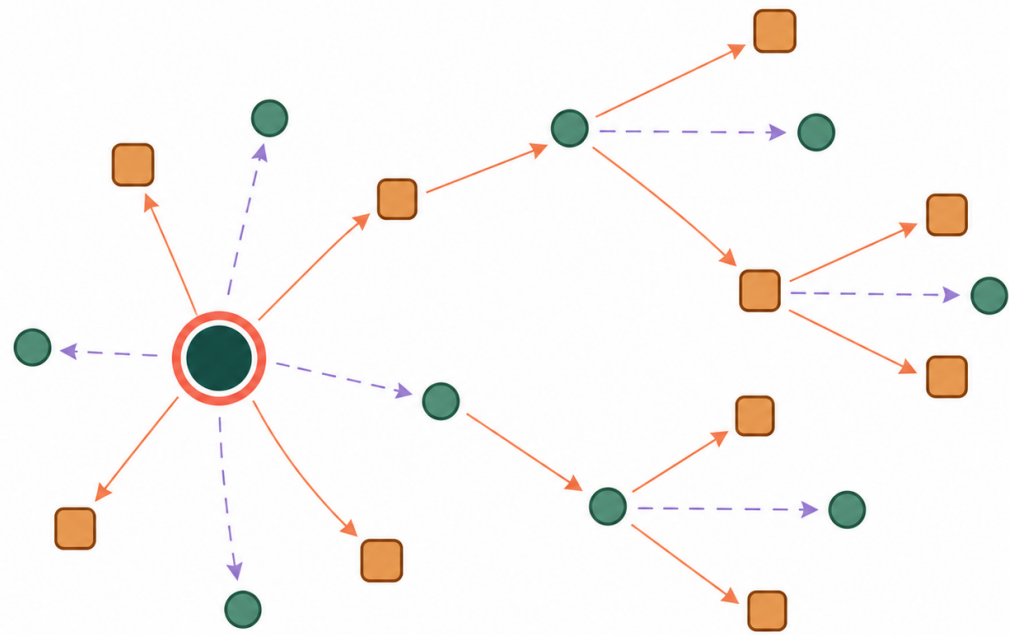
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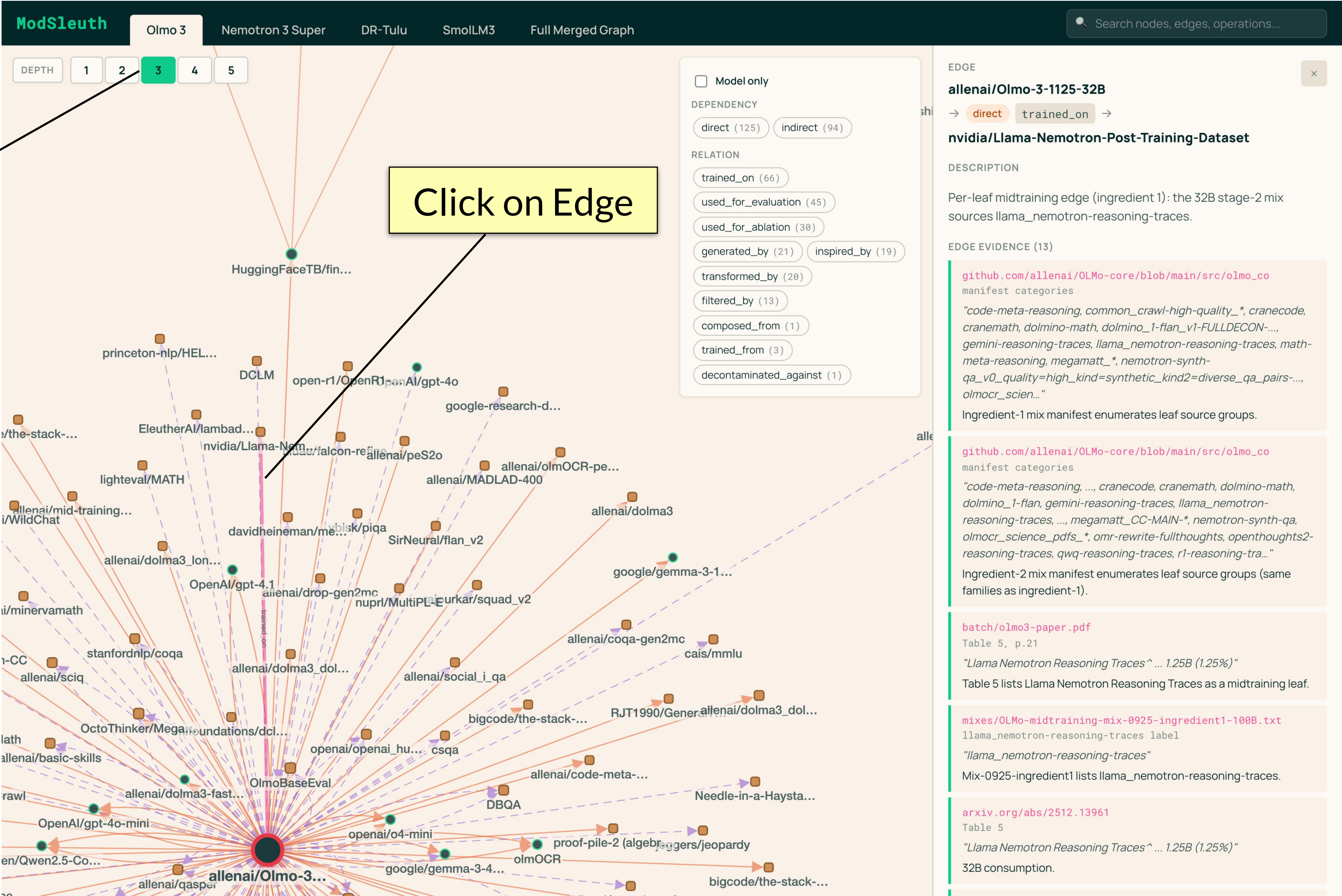
Output of ModSleuth

Recursive Exploration

Click on Edge



Dependency Graph
(All verified)



The screenshot displays the ModSleuth web application interface, which visualizes the training dependencies of a specific AI model. At the top, a navigation bar lists various models: Olmo 3, Nemotron 3 Super, DR-Tulu, SmoILM3, and Full Merged Graph. A search bar is located on the right. Below the navigation bar, a set of buttons allows filtering by depth (1, 2, 3, 4, 5). The main area is a complex dependency graph. A yellow callout box with the text "Click on Edge" points to a specific edge in the graph. Another yellow callout box with the text "Inspect Evidence" points to a panel on the right side of the interface. This panel, titled "EDGE", provides detailed information about the selected edge, including its name (allenai/Olmo-3-1125-32B), its dependency (direct/indirect), its relation (trained_on, used_for_evaluation, etc.), and a list of evidence sources (e.g., github.com/allenai/OLMo-core/blob/main/src/olmo_core/manifest.py, batch/olmo3-paper.pdf).

Part 2: Method

Evaluating ModSleuth

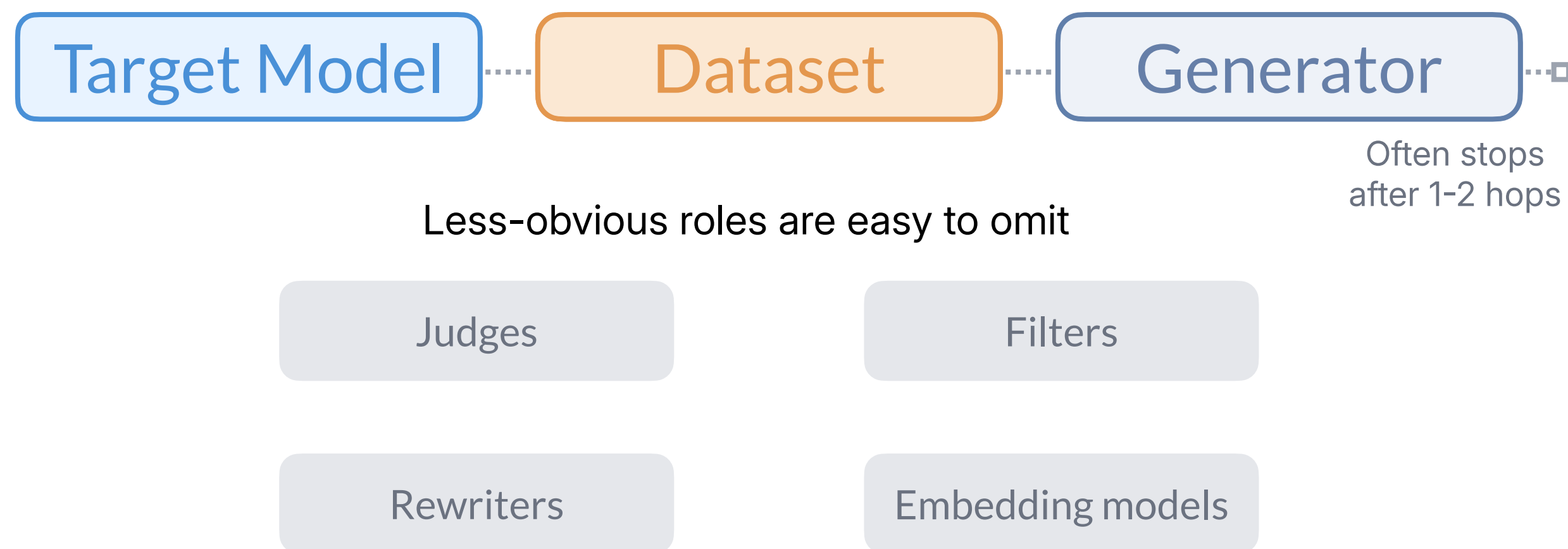
Problem: No complete ground truth

Experts are accurate, but often incomplete

Evaluating ModSleuth

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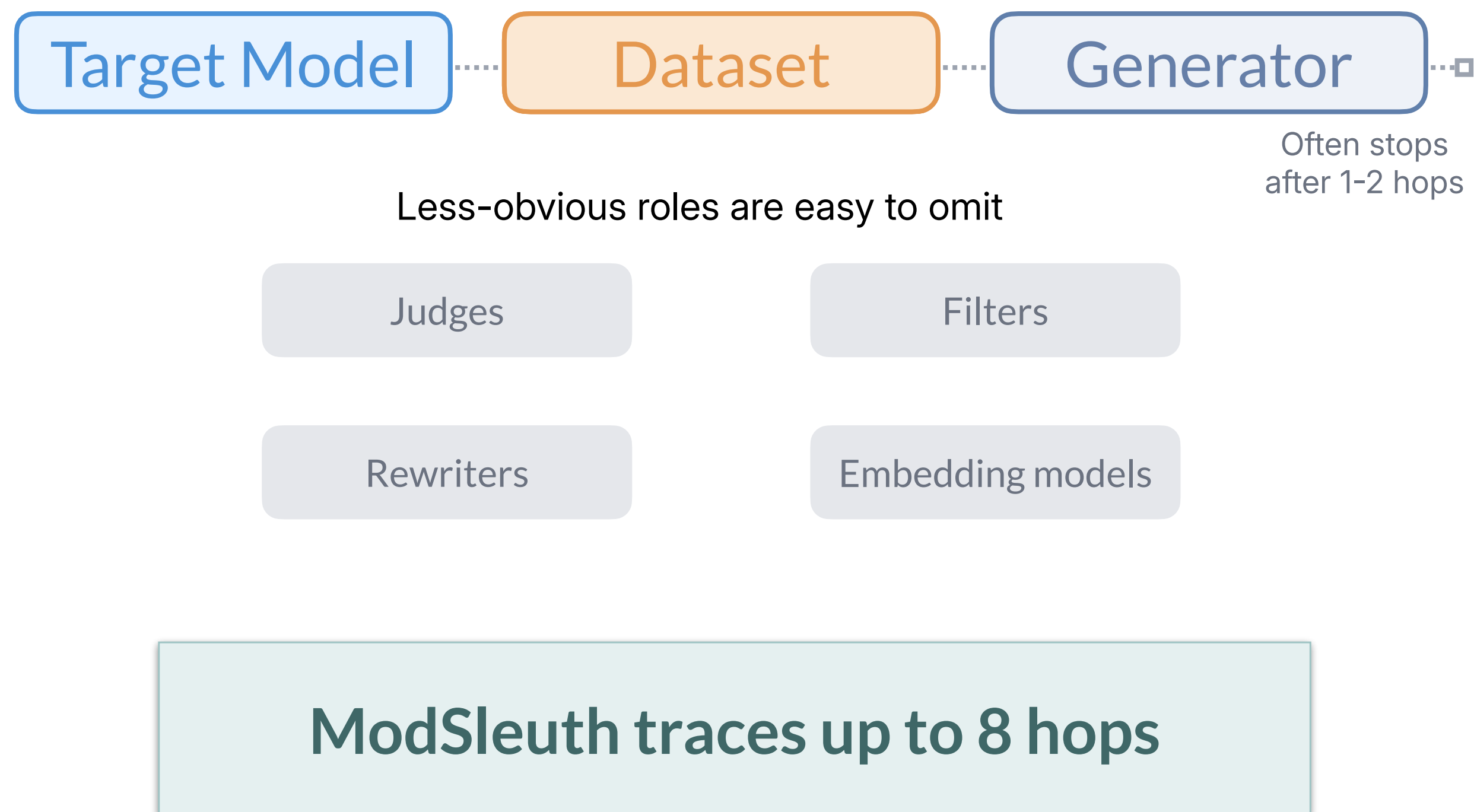
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Evaluating ModSleuth

Problem: No complete ground truth

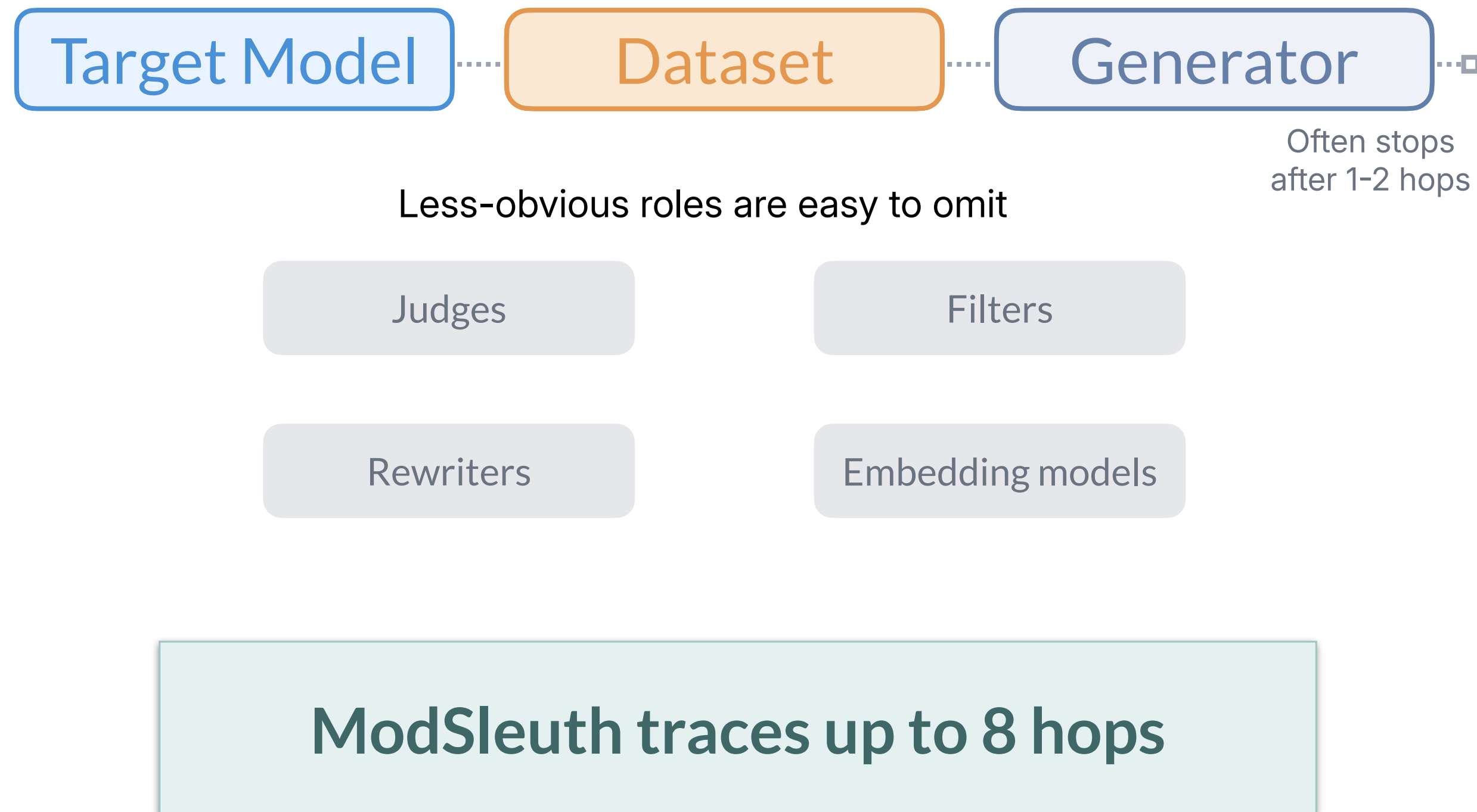
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Evaluating ModSleuth

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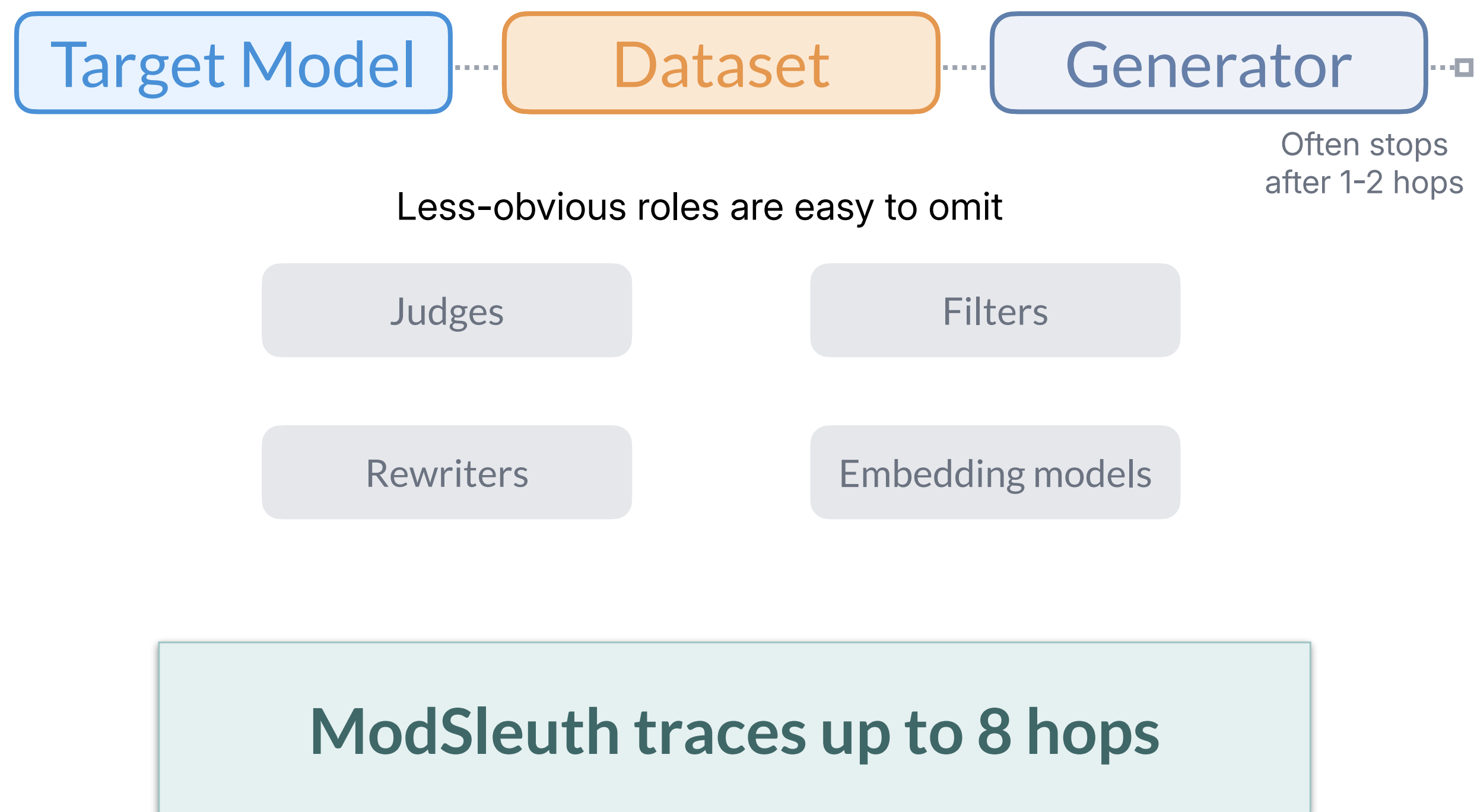
Solution: Evaluate verified recovery

How many correct dependencies
can each system recover?

Evaluating ModSleuth

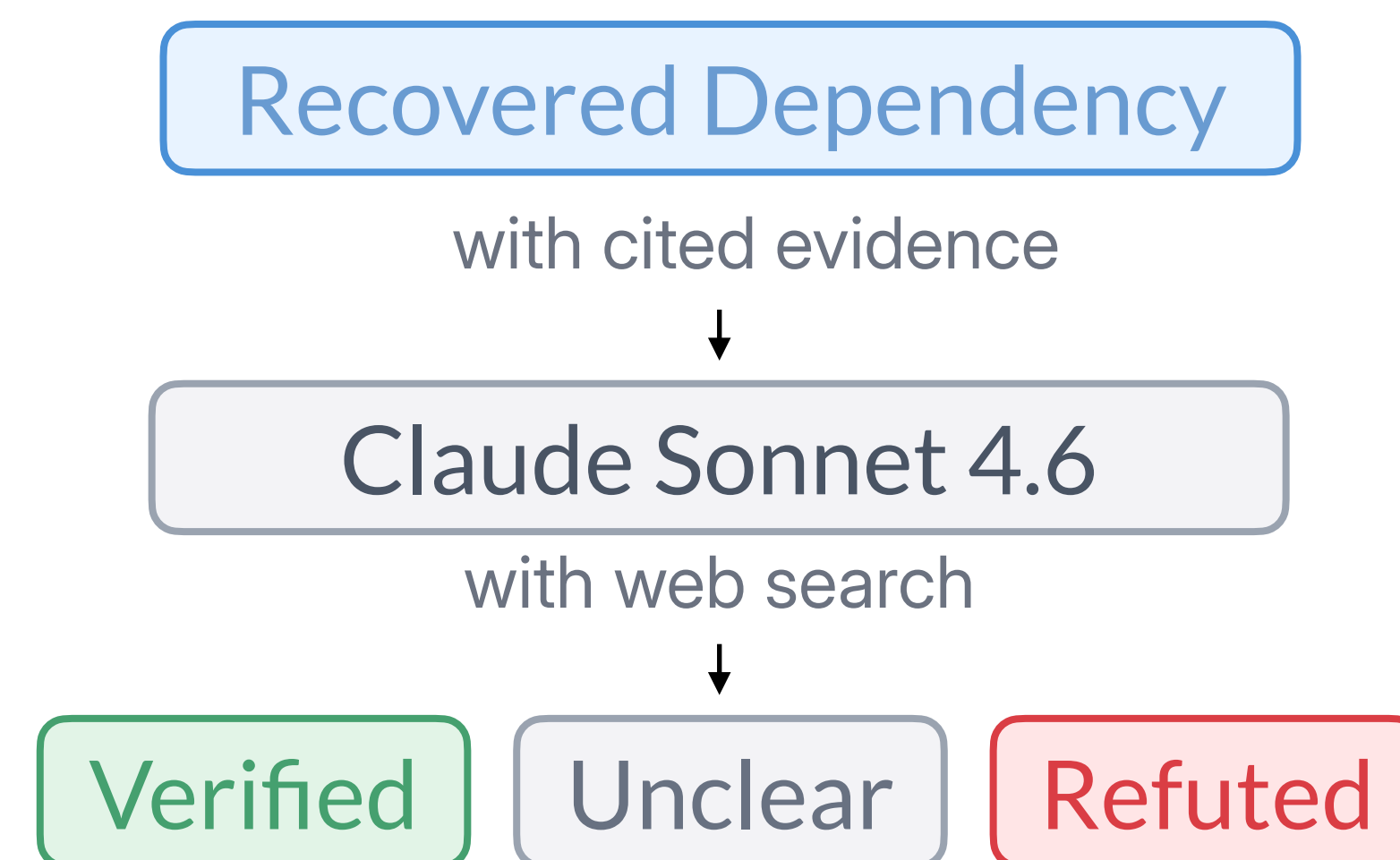
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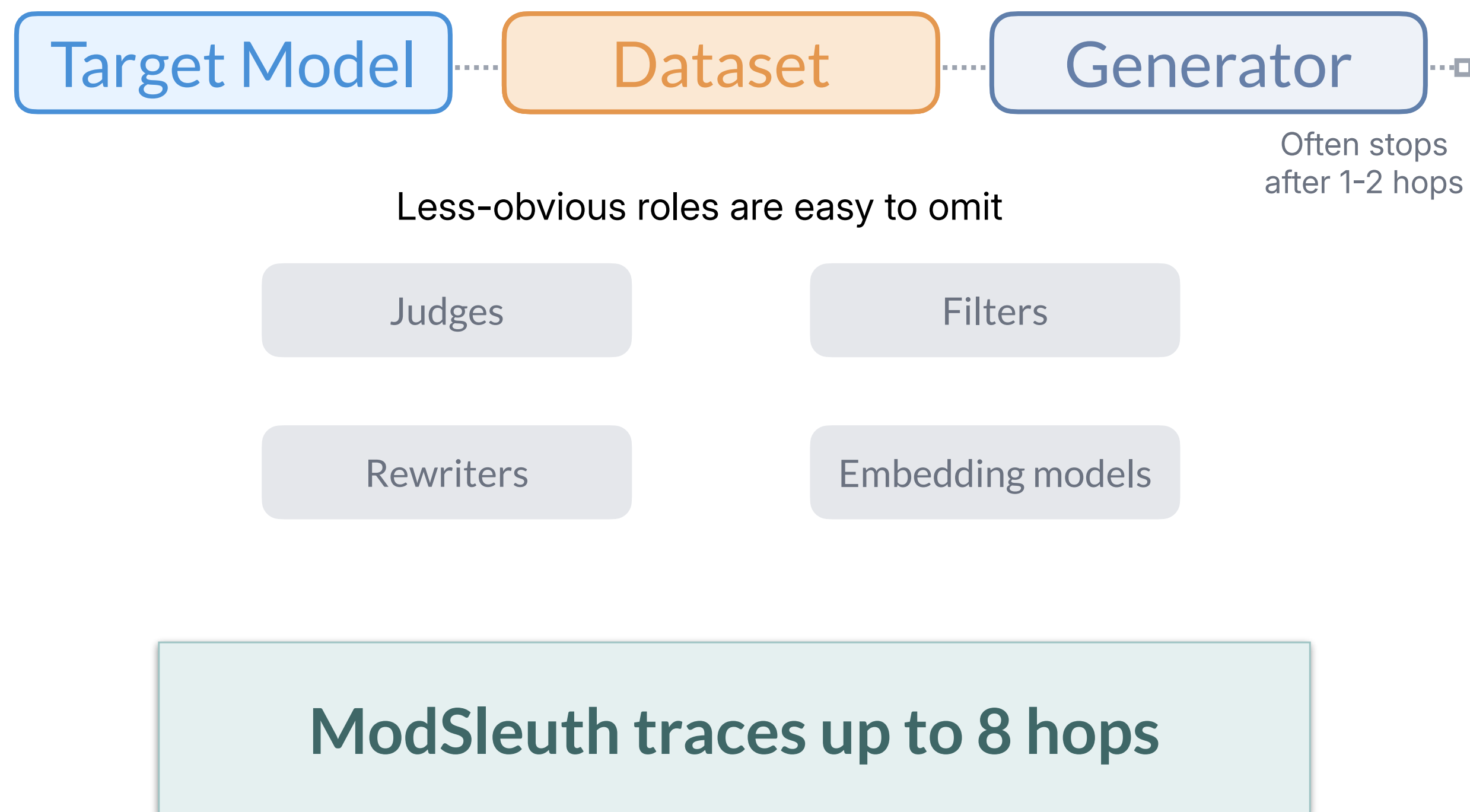
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Evaluating ModSleuth

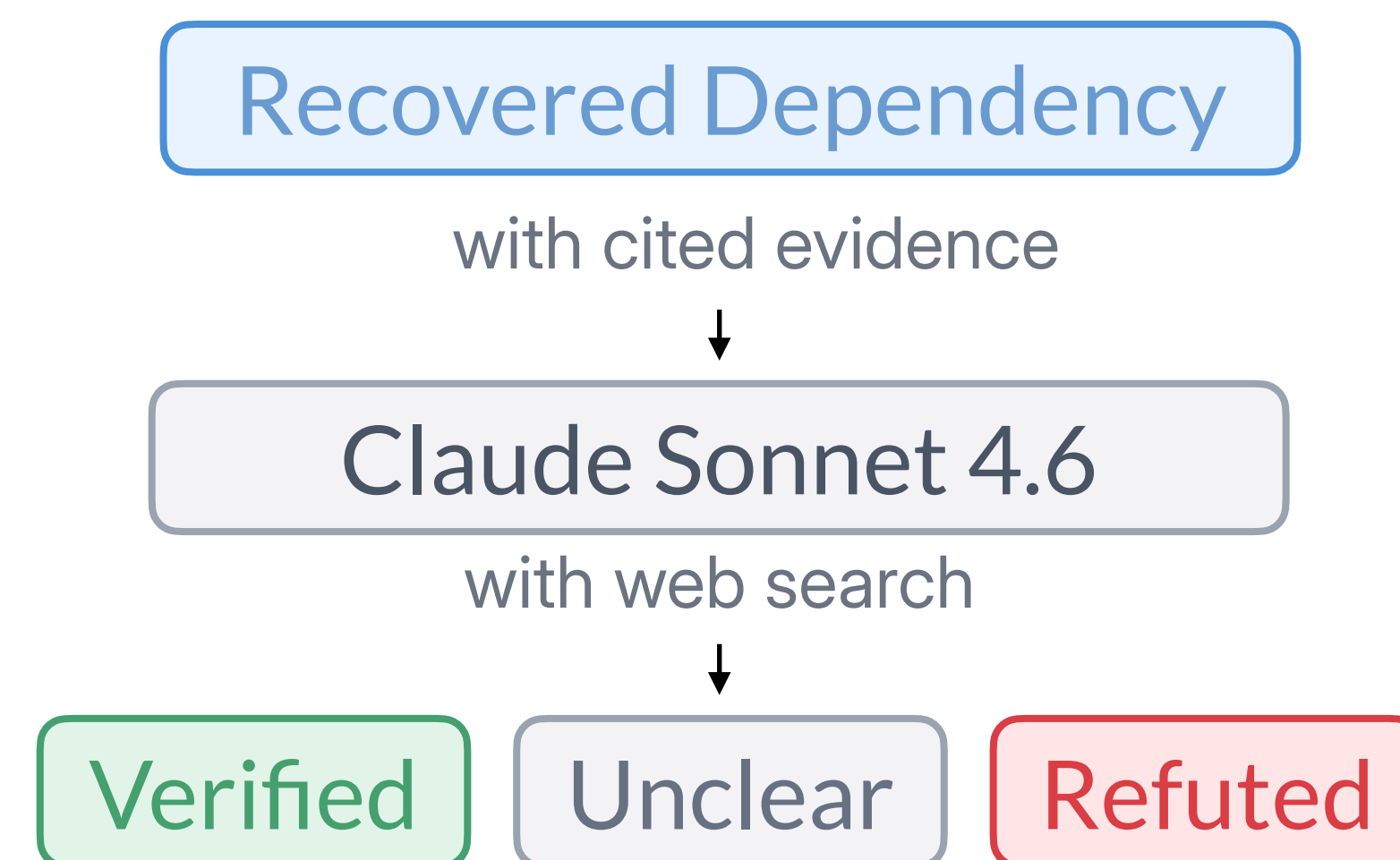
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Key Metric:
verified dependencies recovered

Evaluation Results

	Olmo 3	Nemotron 3	DR Tulu	SmolLM3	Total	
<i>Baselines</i>						
GPT-5.5 Pro	59	156	46	53	314	Strongest Baseline
GPT-5.4 Pro	87	75	44	77	283	
CC-single	91	78	37	69	275	
ChatGPT Deep Research	37	70	28	36	171	
<i>Ours</i>						
ModSleuth (depth-1)	182	237	42	23	484	
ModSleuth (unbounded)	305	613	44	98	1,060	
ModSleuth (BFS reach.) [†]	481	1,023	62	127	1,654	

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ModSleuth (depth-1)	182	237	42	23	484	
ModSleuth (unbounded)	305	613	44	98	1,060	3x Strongest Baseline
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Depth-1 $\subset$ Unbounded $\subset$ BFS-Reachability

Depth-1

Target's own
dependencies

Unbounded*

All dependencies recovered
during target's investigation.

Primary baseline comparison

BFS-Reachability

Full reachable graph

Includes upstream findings

Talk Overview

1. What counts as a dependency, and why is tracing them hard?

Much more than a list of names! Every dependency enters through some operations (generating, filtering), many hops upstream, documented in scattered and ambiguous sources.

2. Can we *automatically* and *reliably* recover the dependency graph from public artifacts?

Yes! ModSleuth, an agentic system we developed, recursively expands the graph and grounds every edge in source evidence—recovering 3x more verified dependencies than baselines.

3. What do the recovered graphs reveal?

Plenty that no single page shows: hidden upstream models, license terms riding along multiple hops, benchmarks on both sides of training and eval, etc.

Quantitative Findings

Audit role	Olmo 3		Nemotron 3		DR Tulu		SmolLM3		Total
	Model	Data	Model	Data	Model	Data	Model	Data	
<i>Direct dependencies</i>									
Training inputs	0	172	0	547	0	11	0	87	813
Upstream operations on training data	85	11	253	13	7	1	7	6	350
Weight-level model lineage	4	0	20	0	3	0	3	0	28
Direct total	89	183	273	560	10	12	10	93	1,191
<i>Indirect dependencies</i>									
Evaluation / ablation	6	163	20	122	8	28	3	10	360
Methodology / audit influence	8	32	24	24	1	3	7	4	103
Indirect total	14	195	44	146	9	31	10	14	463
Grand total	103	378	317	706	19	43	20	107	1,654

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Quantitative Findings

Target	Internal		External		Int. total	Ext. total	Ext. %
	Model	Data	Model	Data			
Olmo 3	13	106	90	272	119	362	75.3%
Nemotron 3	40	203	277	503	243	780	76.2%
DR Tulu	2	9	17	34	11	51	82.3%
SmolLM3	3	28	17	79	31	96	75.6%

An edge is *internal* if its upstream artifact shares the target's organization (e.g. Ai2 artifacts for Olmo 3 and DR Tulu), and *external* otherwise.

75-82% of dependencies come outside the target organization

Key Audit Patterns

Hidden Upstream Models

License-relevant
Paths

Code-level
Provenance

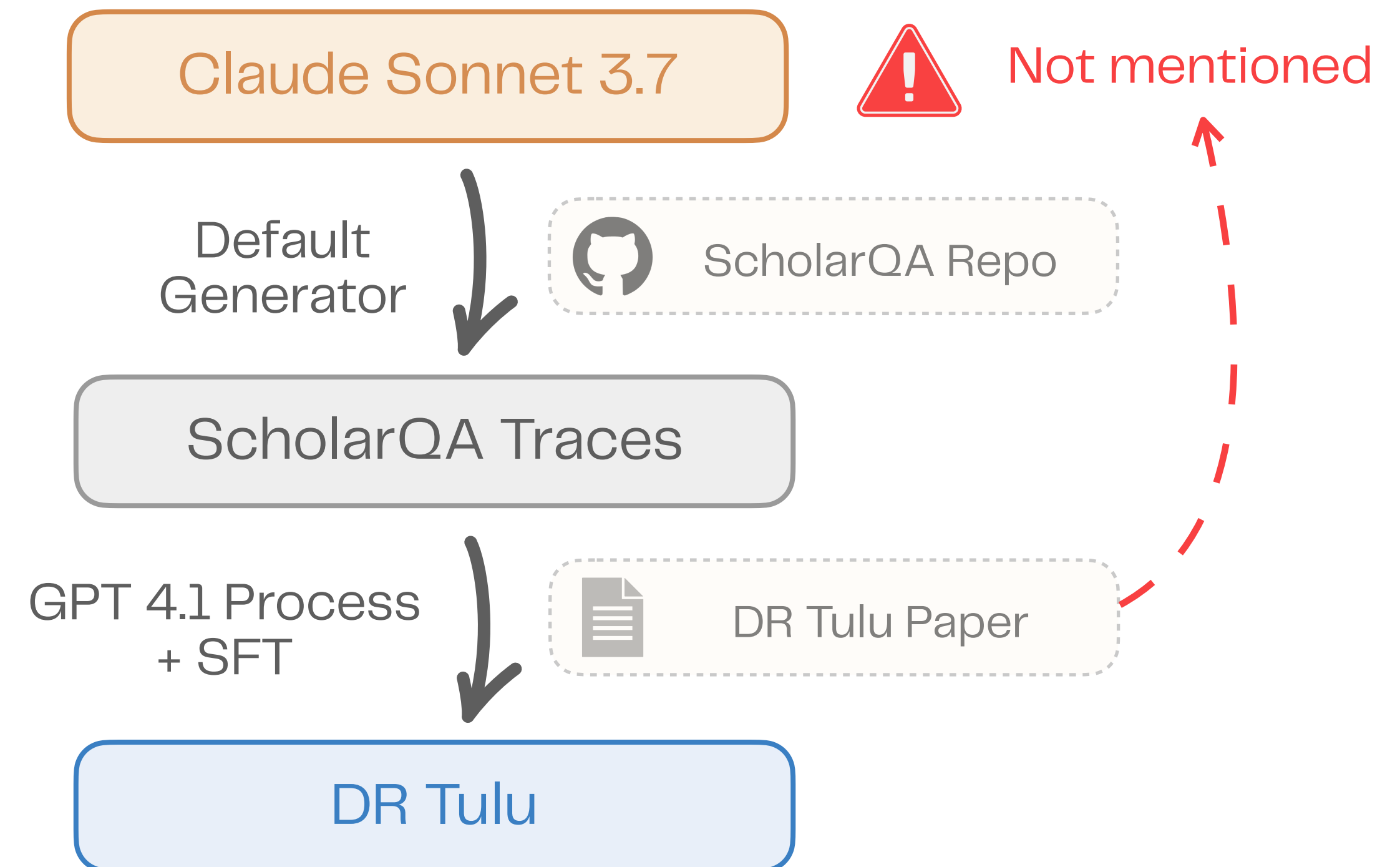
Train-Eval Coupling

Model-mediated
Selection

Good Practices

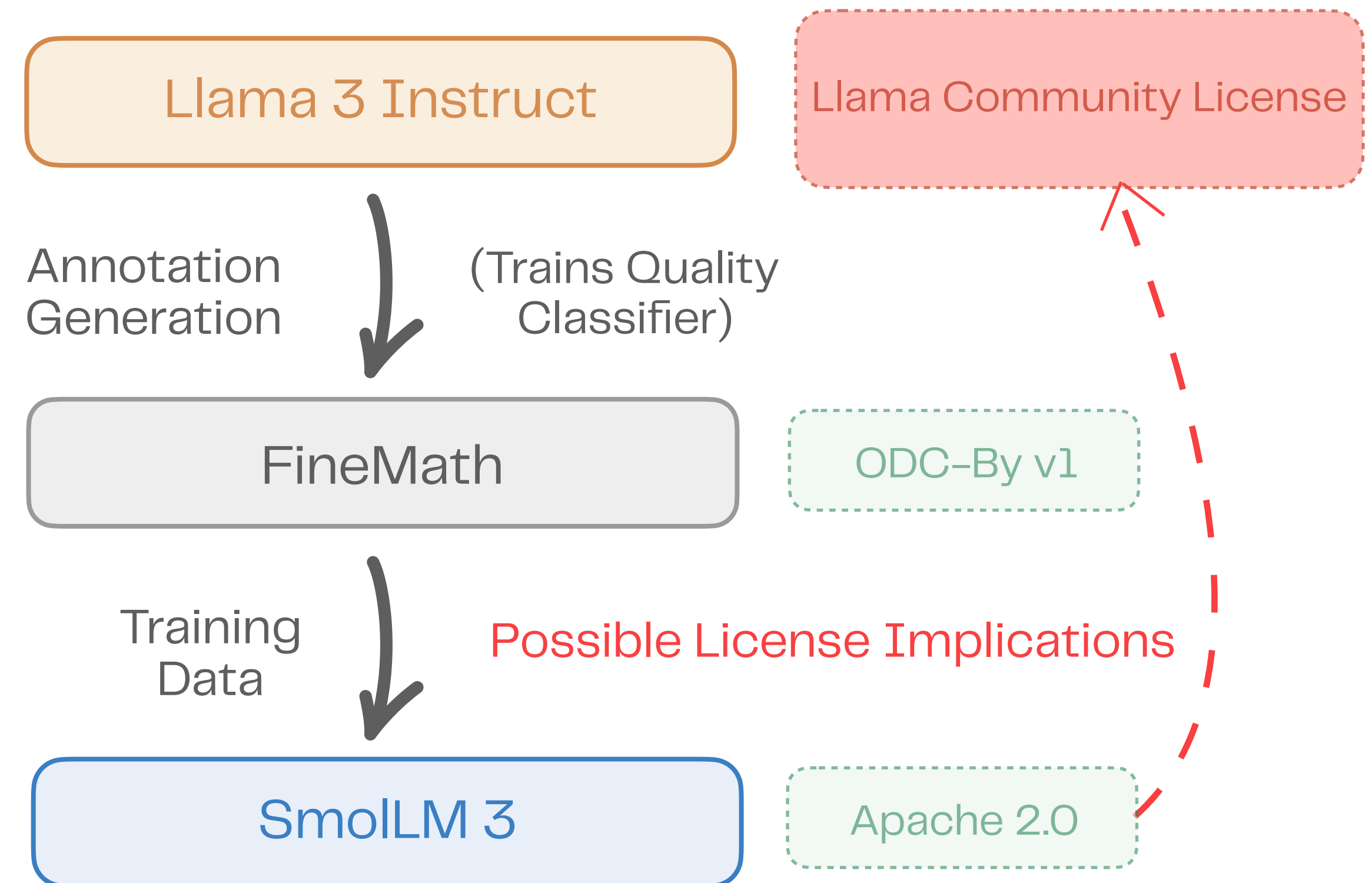
Hidden Upstream Models

Dependencies can be hidden behind intermediate datasets, filters, classifiers, teachers, and tools.



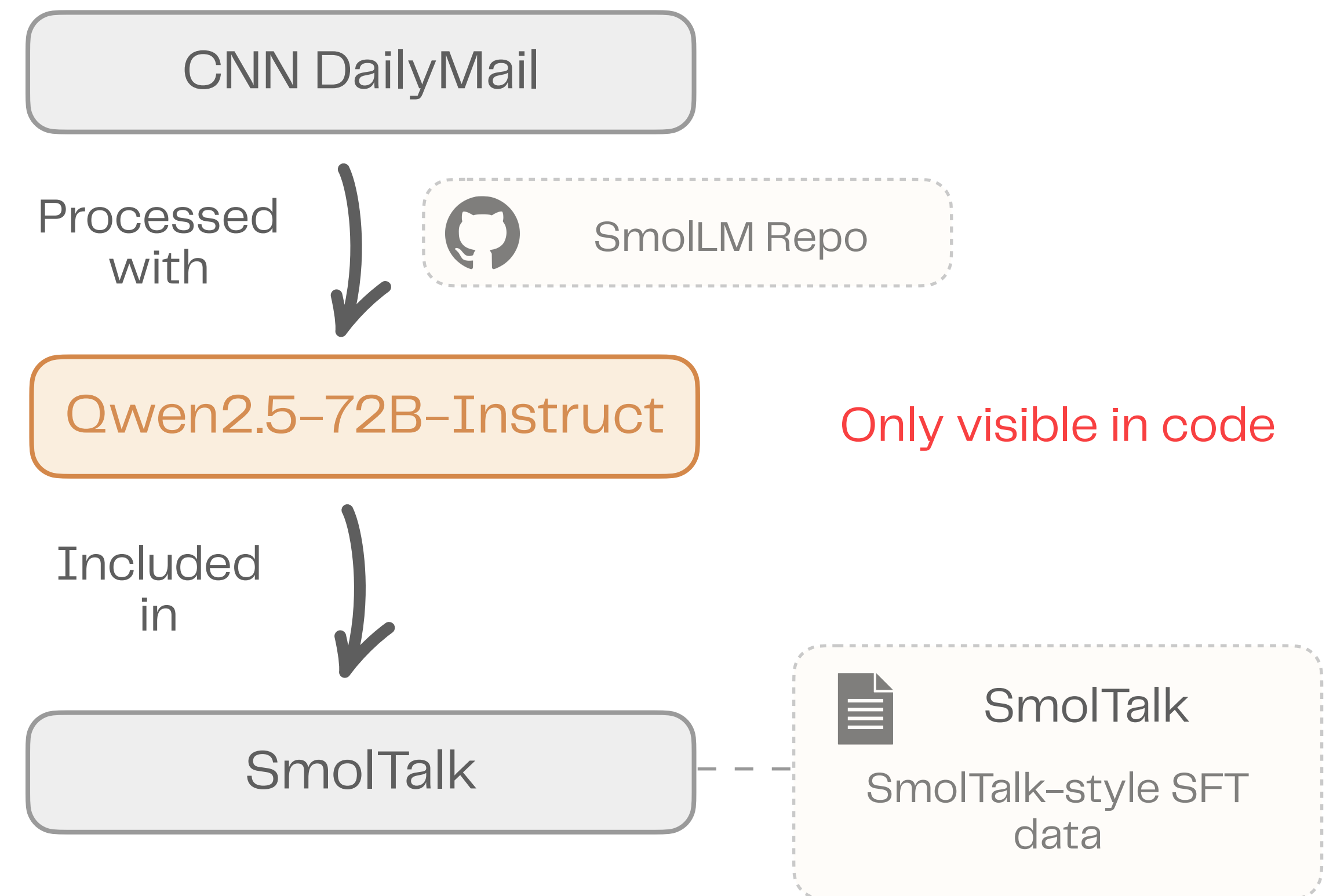
License-Relevant Paths

Synthetic data and annotation pipelines can carry license or terms-of-use implications from upstream models.



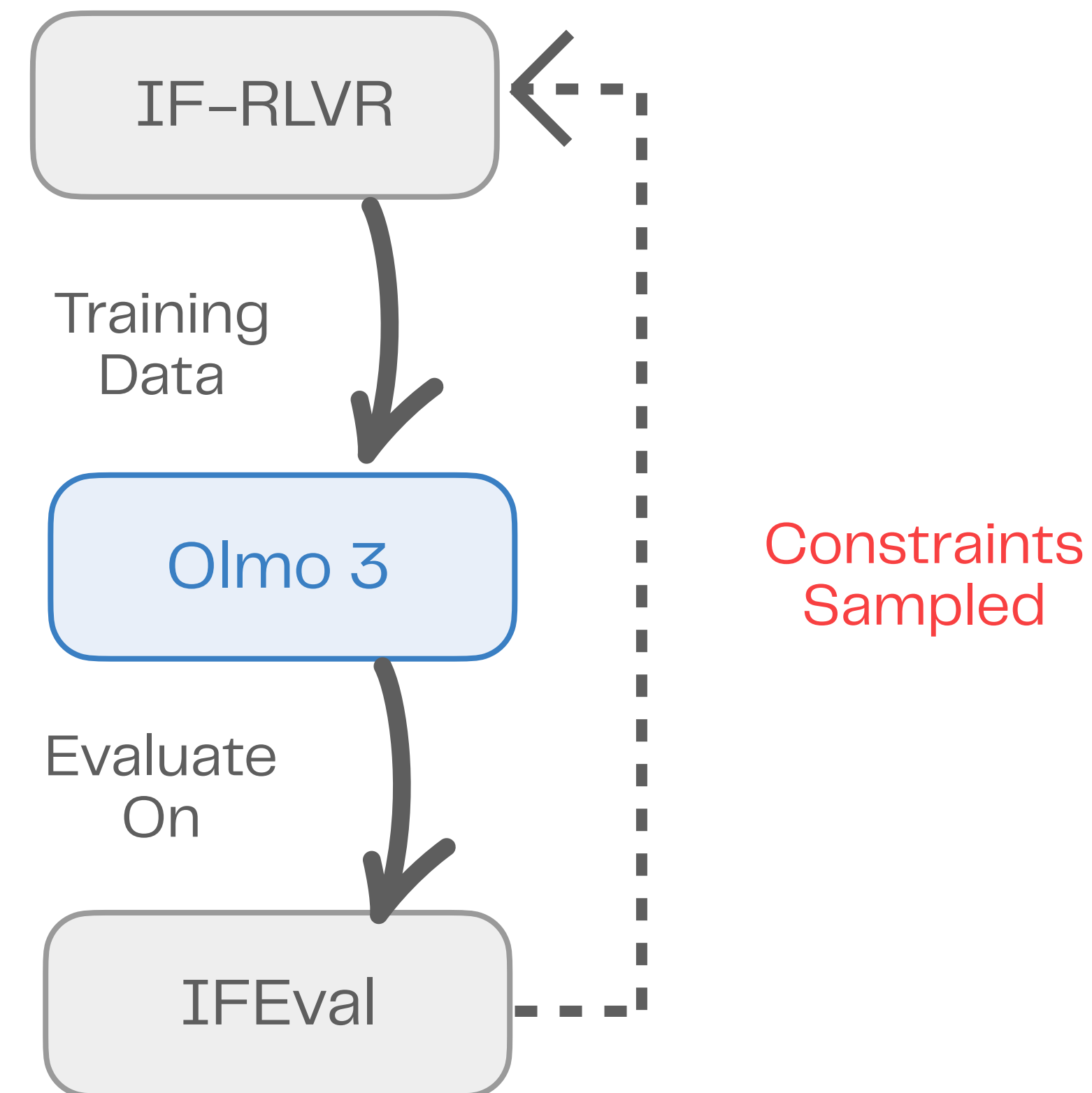
Code-level Provenance

Training scripts, YAMLS, and data-prep code show dependencies hidden by paper/dataset card summaries.



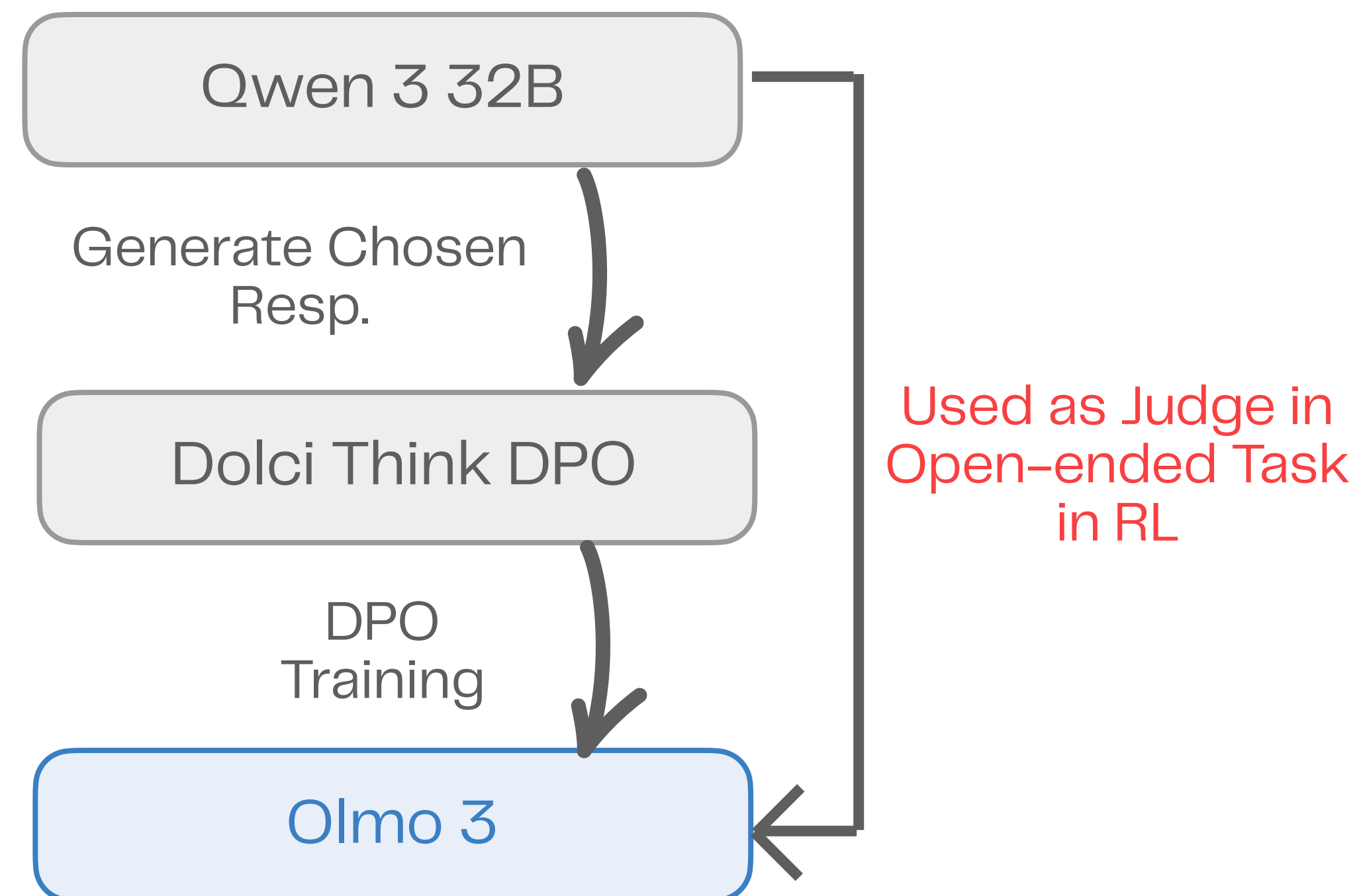
Train-Eval Coupling

Benchmarks can enter the training pipeline as prompts, data, validation environments, or synthetic expansion, then reappear at evaluation time



Model-mediated Selection

Generators, judges, filters,
and reward models decide
which examples are
created, kept, or rewarded.



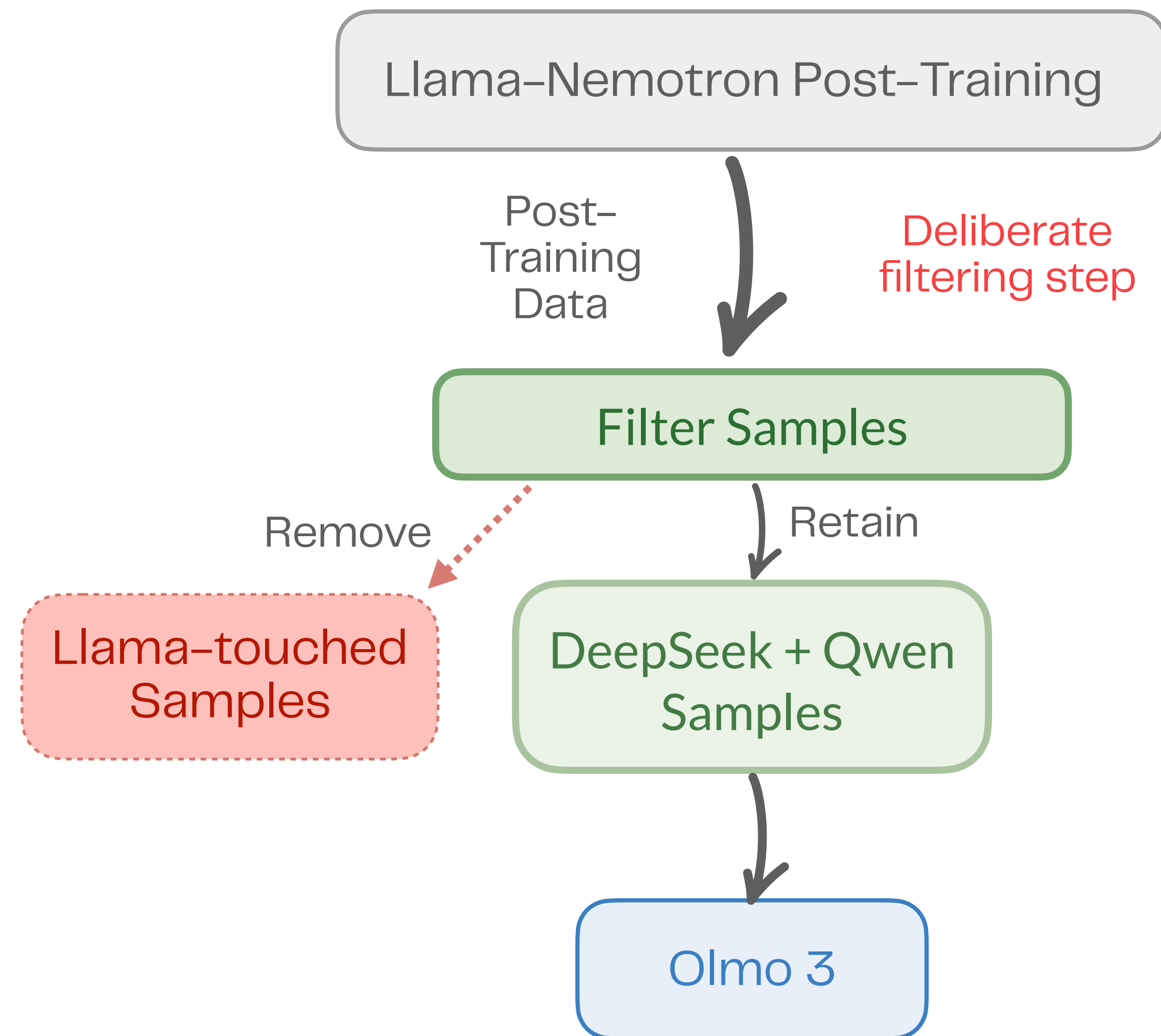
Good Practices

The graph surfaces good practices, not just risks

Permissive teacher swaps

Filtering

Decontamination



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Thanks for listening!



Paper

<https://arxiv.org/abs/2606.12385>



GitHub

<https://github.com/cal-data-audit/modsleuth>



Demo

<https://modsleuth.cal-data-audit.org>



Please leave your kind feedback
at <https://tinyurl.com/modsleuth-fdbk>

