

"They've Stolen My GPL-Licensed Model!": Toward Standardized and Transparent Model Licensing

Anonymous Author(s)

Abstract

As model parameter sizes reach the billion-level range and their training consumes zettaFLOPs of computation, components reuse and collaborative development are become increasingly prevalent in the Machine Learning (ML) community. These components, including models, software, and datasets, may originate from various sources and be published under different licenses, which govern the use and distribution of licensed works and their derivatives. However, commonly chosen licenses, such as GPL and Apache, are software-specific and are not clearly defined or bounded in the context of model publishing. Meanwhile, the reused components may also have free-content licenses and model licenses, which pose a potential risk of license noncompliance and rights infringement within the model production workflow. In this paper, we propose addressing the above challenges along two lines: 1) For license analysis, we have developed a new vocabulary for ML workflow management and encoded license rules to enable ontological reasoning for analyzing rights granting and compliance issues. 2) For standardized model publishing, we have drafted a set of model licenses that provide flexible options to meet the diverse needs of model publishing. Our analysis tool is built on Turtle language and Notation3 reasoning engine, envisioned as a first step toward Linked Open Model Production Data. We have also encoded our proposed model licenses into rules and demonstrated the effects of GPL and other commonly used licenses in model publishing, along with the flexibility advantages of our licenses, through experiments.

CCS Concepts

- **Do Not Use This Code → Generate the Correct Terms for Your Paper;** *Generate the Correct Terms for Your Paper; Generate the Correct Terms for Your Paper; Generate the Correct Terms for Your Paper.*

Keywords

License Analysis, AI Licensing, Automated Reasoning

1 Introduction

In recent years, the compelling generalization capabilities provided by billion-parameter models [44], along with the high computational and data costs associated with their training [25], have motivated ML project developers to collaborate incrementally rather than train models from scratch. For example, a common approach is to download a Pre-Trained Model (PTM) [18] and fine-tune it for downstream task [14]. However, these paradigms may face potential legal risks if the use and redistribution practices violate the governing licenses of the reused components, akin to the GPL violation issues in the field of Open Source Software (OSS) [26]. Another risk arises from the choice of license used to republish the work. Some developers adhere to traditional software publishing practices and select OSS licenses for their models [8, 29], which often lack

clear definitions and conditions regarding ML activities and do not effectively prevent undesirable use. For example, a licensee can close-source your published models, even if they are licensed under GPL, without violating any terms.

There are three possible ways to mitigate above risks. First, developers could avoid using any third-party materials. However, this is extremely difficult for individual developers, as training PTMs is expensive and requires vast amounts of data. For instance, the training dataset for GPT-2 [35] was collected from 45 million web pages, governed by various licenses and terms of use. Second, a new publishing standard for ML projects could be developed, which might include drafting specific licenses for models and datasets [2, 6], along with a compatibility table to guide their reuse policies. However, this approach also has several limitations, as it does little to address existing conflicts in ML projects that already rely on components released under traditional licenses. Furthermore, it is impractical to expect all publishers to relicense their previous works. Third, we can scan the reused components in ML projects and analyze existing license compliance risks to eliminate them. This is a common solution applied to OSS projects [17] but it cannot be directly extended to ML projects. The reason is that ML components can involve complex coupling mechanisms and different licensing frameworks that are interwoven within a project.

Take MixLORA [20] as an example: it is licensed under Apache-2.0 (an OSS license) and is fine-tuned on Llama 2 model [42] (governed by Llama 2 Community License [27], a model license) using the Cleaned Alpaca Dataset [40], which licensed under CC BY-NC-4.0 (a free-content license from Creative Commons, aka CC [5]). Previous OSS license analysis tools [26, 30] that only consider package reference dependencies and focus on software licenses will fall short in such ML scenarios. Therefore, to provide license analysis for ML projects, the key is to develop a specific ontology that describes the ML workflow and provides a corresponding interpretative solution for licenses, covering all licensing frameworks and disambiguating their mapping rules related to ML activities. Moreover, the lack of consensus in standard model publishing practices and the inflexibility of existing publicly available model licenses have led many developers to publish their models under OSS licenses or even free-content licenses [4, 13], further complicating the design of license analysis methods.

In this paper, we propose a two-pronged approach to address these challenges. First, to resolve existing noncompliance in ML projects, we introduce *MG Analyzer*, a tool that constructs ML workflows as Resource Description Framework (RDF) [31] graphs and assesses potential license compliance issues, improper license selection, granting of rights, restrictions, and obligations within the projects. Second, to promote standardized model publishing in the future, we propose a new set of model-specific licenses, *MG Licenses*, offering CC-style licensing options for developers to choose from. To present potential risks of using traditional OSS,

model, and free-content licenses in model publishing scenarios, we evaluate them with the *MG Analyzer* on a typical workflow. We also demonstrate the flexibility of *MG Licenses* in encompassing nearly all licensing conditions provided by other model licenses through comprehensive comparisons.

The main contributions of our paper are:

- We identified the challenges of license compliance and model licensing in ML projects.
- We developed MG Analyzer based on semantic technologies to enable automated reasoning for license analysis in ML projects. It incorporates a dedicated vocabulary capable of describing ML workflows with complex dependencies and the rules of OSS, data, and model licenses. We also provide a interface to convert user-input workflow descriptions into RDF graphs following this vocabulary. Based on these graphs, MG Analyzer constructs dependencies, performs reasoning, and detects potential license conflicts.
- We drafted a set of model licenses called MG Licenses to promote more standardized model publishing. These licenses are well-defined and cover a complete spectrum of model publishing scenarios. Furthermore, we have integrated support for MG Licenses within MG Analyzer.
- To the best of our knowledge, MG Analyzer and Licenses represent the first attempt at standardizing model publishing. The proposed code and license drafts are available at ([link temporarily hidden due to double-blind policy](#)).

The rest of the paper is organized as follows. Section 2 presents the motivation for this work, drawing on related studies and background. Section 3 introduces our proposed vocabulary for workflow descriptions and the license analysis tool. Section 4 offers a comprehensive comparison of commonly used licenses and briefly outlines the advantages of the new model licenses we propose. Section 5 presents license analysis results to demonstrate the risks associated with non-standard licensing, while Section 6 concludes the paper. Supplementary tables and codes are provided in the Appendix.

2 Background and Related Work

2.1 License Compliance Analysis

The previous license compliance analysis studies primarily focus on OSS-licensed software [7, 39], and several successful tools, such as FOSSology [17] and Black Duck Software Composition Analysis [16], have been developed. The main goal of these tools is to identify all open-source dependencies in software projects to evaluate associated license compliance risks, obligations, and attribution requirements. Typically, the component dependencies and license information in a software project can be obtained through scanning and matching [30]. This process involves gathering information from notices, headers, licenses, and other project files or attempting to match the code to determine its provenance. Unfortunately, these strategies cannot be naturally extended to ML projects for the following reasons.

First, the components of ML projects, particularly models, have more intricate dependencies than code. For example, knowledge can be transferred between models without explicitly copying weights [46]. Second, the OSS Bill of Materials standard, such as

Software Package Data Exchange (SPDX) [10], does not fully support common model licenses like OpenRAIL-M [6], Llama 2 [27]. Third, non-standard licensing (model publishing under OSS or free-content licenses) is prevalent in ML projects [9], adding complexity to license analysis. Furthermore, the crowd-sourced nature of ML components may also lead to over-permissive licenses [36], distorting the analysis results.

For these reasons, license compliance issues in the ML field remain nearly unexplored. Rajbahadur *et al.* [36] investigated license provenance issues in ML datasets and found instances of non-compliance between their licenses and the licenses of their data sources. Building on these findings, Duan *et al.* [9] proposed a tool that analyzes conflicts directly based on the licenses of data sources and provided guidelines to minimize such conflicts. However, their tool is limited to generating analysis reports and lacks the ability to visualize and exchange ML workflows, making it difficult to extend or integrate external resources from the web (e.g., linking to another workflow via URI). Therefore, in this work, we propose an ontology describing ML workflows using RDF graphs (a visualized workflow is provided in Appendix D), making it both extensible and linkable, and then analyze license compliance through an automated reasoning engine.

2.2 Model Licensing

Today, we have many OSS licenses to accommodate diverse publishing scenarios [38]. However, do they still function as intended in model publishing scenarios? The answer is no. While these licenses aim to govern the use and distribution of software, they lack definitions of ML concepts, which compromises their effectiveness (ref. Section 4). Some model licenses (or agreements) are also emerging, such as Llama 2 and Gemma [24]. However, most of these licenses are specifically designed to govern certain models or their derivatives and are not as open as they claim to be [22]. Meanwhile, Contractor *et al.* [6] proposed OpenRAIL-M, a model license derived from Apache-2.0. While this license offers good clarity, it enforces use behavior restrictions that render it non-compliant with open-source licenses like GPL-3.0 [12]. In addition, although OpenRAIL-M has many variations, its license terms are quite homogenized and lack the flexibility needed to accommodate different model publishing scenarios, such as non-commercial use, open sourcing, and restrictions on sharing outputs. Therefore, a significant number of developers have opted to publish their models using CC licenses, such as CC-BY-NC-4.0, as an alternative to prohibit commercial use of their models. However, these licenses also face the issue of losing effectiveness in the context of model publishing. Such unstandardized licensing practices can lead to increased compliance issues and pose potential legal hazards in ML projects [9]. To promote standardized model publication, we propose a new set of model licenses that provide a wider range of licensing options.

3 MG Analyzer

This section aims to introduce the specific design of MG Analyzer by exploring three questions: (i) *How can we represent the workflows of ML projects?* (ii) *How do we establish a mapping from license text to reasonable rules?* (iii) *What types of license compliance issues can*

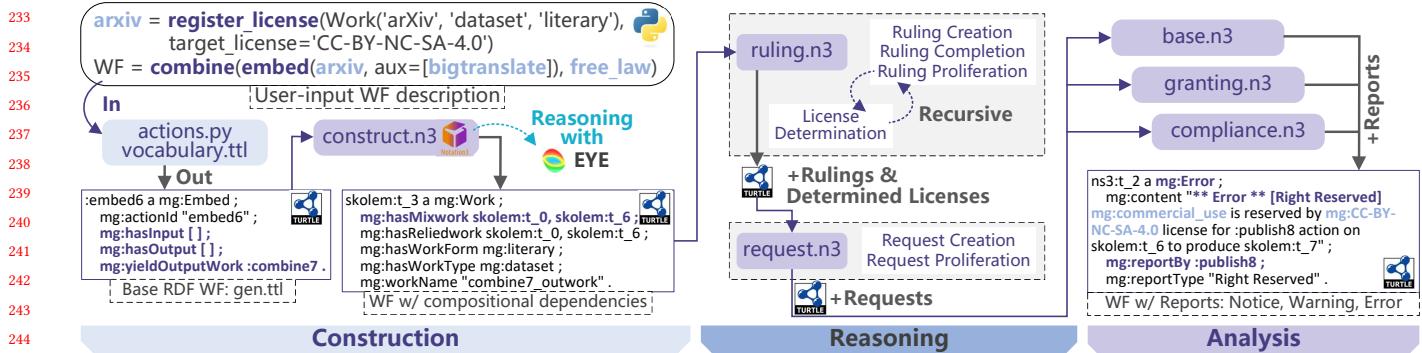


Figure 1: Overview of MG Analyzer. ("mg" is the prefix for our proposed vocabulary.)

arise in ML projects, and how can we detect them? Before delving into the detailed design that answers these questions, we first provide an overview that serves as a roadmap for this section. As illustrated in Figure 1, the process of MG Analyzer is divided into three main parts: Construction, Reasoning, and Analysis.

In the **Construction Stage**, user-input workflow descriptions (written in Python) are converted into an RDF graph (saved as `gen.ttl` in Turtle format) that contains the base information of the workflow. This conversion is achieved with the help of RDFLib [19] and the *MG Vocabulary*, which is part of our analyzer. RDFLib provides an API for writing RDF graphs, while the MG Vocabulary defines the specific semantics to represent the concepts and dependencies in ML projects. Then, we apply reasoning rules (written in Notation3 [1]) for the complete workflow construction using the EYE reasoner [43]. The reasoner concludes new properties that represent the input and output chains between components, followed by further reasoning to identify the *compositional dependencies* among them (reflecting Question (i); see Section 3.1 for details).

The main tasks in **Reasoning Stage** involve concluding the *definition dependencies* and *rights-using* dependencies. This is achieved through two substeps. First, a new property called *ruling* is created to record the definition of the output work in relation to the input work within the context of licensing. For example, if we merge GPL-licensed code into another software, the resulting work is considered a *derivative* of the original work. This relationship, which we refer to as *definition dependencies*, is crucial for determining the applicable license of the output work. We recursively identify such dependencies and ascertain the licenses of indeterminate works until all works in the workflow have a license. Based on the RDF workflow graph with complete license assignments, we can execute the second step of reasoning, called *request*, which infers *rights-using* dependencies that represent the rights required for the work according to practical reuse methods (reflecting Question (ii); see Section 3.2 for details).

So far, all necessary information for license analysis has been concluded before entering the final **Analysis Stage**. In this stage, MG Analyzer evaluates the validity of the base workflow information, checks for the satisfaction of rights granting, and assesses license compliance and conflicts. Entities of the class *Report* are generated to present these results in RDF format (reflecting Question (iii); see Section 3.3 for details).

3.1 ML Workflow Representation

The representation of ML workflows, particularly when considering license analysis scenarios, differs significantly from common software workflows for the following three reasons.

① ML workflows often involve various components (e.g., code, datasets, images, model weights, services), each governed by licenses from different frameworks. Additionally, non-standard licensing practices are prevalent in current ML projects [9, 36], for instance, the C4AI Command R+ model [4] is licensed under a free-content license: CC-BY-NC-4.0. Therefore, the representation should be flexible enough to cover such situations.

② The component dependencies in ML workflows may be implicit and nested. For instance, Openjourney [34] is fine-tuned based on StableDiffusion [37] model and the data generated by Midjourney [33]. In this case, knowledge from Midjourney is transferred to Openjourney without explicit compositional inclusion. Therefore, the representation should consider the multifarious dependencies present within ML projects.

③ The components' dependencies are also defined by the components' practical licenses and the ways they are reused. A common case in the OSS field is that republishing Software as a Service (SaaS) is considered to convey a *derivative* under AGPL-3.0 but has *no definition* under GPL-3.0. Therefore, terms like *derivative* and *independent* should be contextualized within specific licenses, and our representation should be capable of reflecting such meanings.

Therefore, we propose the MG Vocabulary to describe the properties and classes within ML workflows. For the flexibility issue ①, we use the following terms to abstract key concepts of ML workflows:

Work: Represents the components (e.g., models, datasets), each with a unique Type and Form. A work can have a license assigned through a Register License Action, or its license can be determined through rules applied in the Reasoning Stage (ref Figure 1).

Action: Represents operations performed on a Work, including Modify, Train and Combine, etc. In practice, we broaden the definition of these operations to make the vocabulary adaptable to different types of works. (See Table 1 for more details.)

Work Type: Includes software, dataset, model, and mixed-type. It is used to describe both the nature of the work and to identify the types of materials intended by a license. We utilize this information to detect mismatches between a work's type and its license.

349 **Work Form:** Divided into three subclasses: Raw, Binary, and Service
 350 to provide flexibility. For example, source code, model weights,
 351 and corpus fall under Raw; compiled programs are considered Bi-
 352 nary; and SaaS or online chat LLMs are categorized as Service.
 353 Additionally, three general terms are offered: raw-form, binary-
 354 form, and service-form, which can work in conjunction with the
 355 work type. This approach helps represent concepts that lack a for-
 356 mal designation, such as "a dataset published as a service". We use
 357 mixed-form to represent the cases involving collections of works.

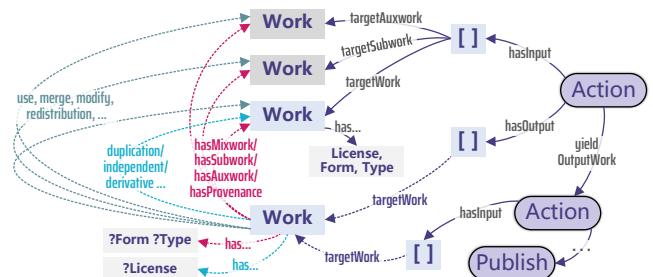
358 **LicenseInfo:** This contains the essential license information
 359 derived from conditions, including the license name, ID, intended
 360 types of works, whether it is copyleft or permissive, as well as
 361 granted and reserved rights, etc. While the license name is sufficient
 362 to describe the base workflow, to enable reasoning, LicenseInfo
 363 should bind rules, which we will discuss in the next section.

364 At this stage, we can describe a base ML workflow, as illustrated¹
 365 schematically in Figure 2 (The RDF graph can be referred to in
 366 *gen.ttl* in Figure 1). In this base workflow, the derived input and
 367 output of each Action can be represented as blank nodes, serving
 368 as placeholders. These placeholders will be populated by reasoning
 369 the output yielded by the previous action and the input for the
 370 current action, respectively.

371 For dependency issues discussed in ② and ③, we identify three
 372 potential types of dependencies in an ML project: **compositional**,
 373 **definition**, and **rights-using**. These dependencies are visually
 374 represented by different colored dashed arrows in Figure 2. *Com-
 375 positional dependencies* are categorized into four types: *Mixwork*,
 376 *Subwork*, *Auxwork*, and *Provenance*, each representing the contain-
 377 ment relationships between input and output works. For example,
 378 when the output work includes the input work or a part of it, the
 379 input is considered the Mixwork of the output. This type of depen-
 380 dency is vital for license analysis because all actions performed
 381 on the output work, including any rights usage, will proliferate
 382 to the Mixwork components. For instance, when fine-tuning an
 383 ensemble model [11], the fine-tuning operation will cascade to all
 384 submodels. Consequently, the license terms related to fine-tuning
 385 for each submodel are triggered, meaning that any constraints or
 386 rights imposed on the submodels must be honored. Additionally,
 387 if a work includes Mixworks in different forms, such as code and
 388 weights, we need to generalize the output's form to raw-form to
 389 accommodate these variations. A similar approach applies to the
 390 work type as well. Subwork and Auxwork are used to track works
 391 that are utilized by other works in the workflow, such as training
 392 datasets or distilled models. The key distinction is that Subwork is
 393 intended to be published alongside the output, which necessitates
 394 additional license analysis related to republishing. Provenance is
 395 specifically used for the Register License action to indicate that the
 396 output is simply the input itself, bound to a license. In such cases,
 397 any further proliferation of dependencies should cease.

398 The *definition dependencies* represent the relationships between
 399 works based on the definitions established by their licenses. For
 400 example, if a new work is created by modifying GPL-licensed code,
 401 that modification is considered a *derivative* of the original work.
 402 These dependencies should be understood in the context of the
 403 original license and can extend to subsequent actions if the same

404 ¹ The "mg" prefix is omitted and some properties are merged or filtered for presentation.



405 **Figure 2: A Typical ML Workflow Represented by MG Ana-
 406 lyzer.** Dashed arrows with different colors indicate properties
 407 related to three types of dependencies: **compositional**, **de-
 408 finition**, and **rights-using** dependencies.

409 conditions are activated again (e.g., a *derivative* of a *derivative* is
 410 likely still a *derivative*). These dependencies are the main factor
 411 in determining the applicable license and restrictions for the out-
 412 put work. For example, if the original work is under GPL-3.0, the
 413 republication of *derivatives* must also apply the GPL-3.0 license.
 414 Additionally, a work may have multiple definition dependencies in
 415 a complex workflow, and these dependencies should be simultane-
 416 ously satisfied during license determination (if possible; otherwise,
 417 an error should be reported). The corresponding implementa-
 418 tion in the MG Analyzer is illustrated in the *Reasoning Stage* of Figure 1.
 419 New instance nodes called *Ruling* are created to track the definition
 420 dependencies and triggered rules for each work, determining their
 421 applicable licenses in an alternating manner.

422 The *rights-using dependencies* describe the rights that must be
 423 granted for actions performed on works. For example, when exe-
 424 cuting a Train action on a model, it requires the rights to *use* and
 425 *modify* (termed as *Usage* in MG Vocabulary) from the model's li-
 426 cense². Similarly, the rights-using dependencies should proliferate
 427 according to compositional dependencies. For instance, the re-
 428 quirement to *modify* a model extends to all its submodels. In the MG
 429 Analyzer, we create new nodes called *Request* to represent this
 430 dependency. Additionally, it is insufficient to only check the grant-
 431 ing rights; the reserved rights must also be verified. Depending on
 432 the clarity of the license text, some rights may either be explicitly
 433 granted or reserved. Furthermore, certain license clauses can waive
 434 the requirement for specific rights. For instance, both GPL-3.0 and
 435 CC licenses include automatic relicensing clauses for downstream
 436 recipients, which eliminate the need for a *sublicense* right.

437 By MG Vocabulary, we are able to describe complete ML work-
 438 flows and represent the necessary dependencies for license analysis.
 439 The *compositional dependencies* are license-independent and can
 440 be reasoned from the base workflow. However, *definition de-
 441 pendencies* and *rights-using dependencies* are associated with specific
 442 rules expressed in natural language within each license. To facilitate
 443 automated reasoning for these dependencies, the next step is to
 444 develop a viable method for encoding license terms into formal
 445 logic rules.

446 ² An example of such rights granting can be found in the Llama 2 Community License,
 447 which states, "You are granted a ... to use, reproduce, distribute, copy, create derivative
 448 works of, and make modifications to the Llama Materials."

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**Table 1: Supported Actions in MG Analyzer Following Rule
Alignment. The symbols = and ≈ indicate that the Type/Form
of output work and input work are the same and may differ,
respectively. The corresponding OSS, Free-content, and
Model license terms for each action are listed.**

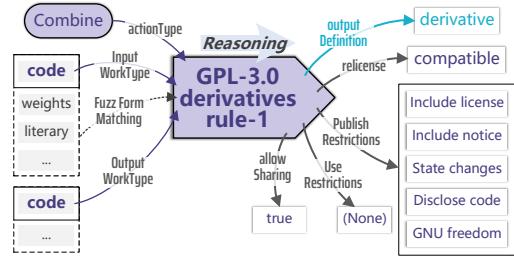
Action	Type	Form	Composition	Terms
Copy	=	=	Output and input are exactly same .	Copy Duplicate
Combine	≈	≈	Entire input included in output.	Link Aggregate MoE Arrange Collect
Modify	=	=	Output includes a significant portion of input and can be reverted.	Modify Fine-tune
Amalgamate	=	=	Output includes portions of input but cannot be reverted .	Modify Remix Fusion
Train	=	=	Output has the same structure as input and may contain a negligible portion of it.	Alter Adapt Train
Generate	≈	≈	Output does not contain any portion of input and may perform differently from it.	Output Generate Synthetic
Distill	=	=	Output does not contain any portion of input but performs similarly to it.	Distill Transfer Extract
Embed	=	=	Output does not contain any portion of input, but there is a mapping that converts input to output.	Transmute Transform
Publish	=	≈	Output is the same as the input but may have a different form.	Redistribute Perform Display Disseminate

3.2 License Rule Encoding and Reasoning

484 Typically, licenses are designed to govern the use and distribution
485 of specific types of works. For example, GPL-3.0 is tailored
486 for source code and object code, while CC licenses focus on literary,
487 musical, and artistic works. As a result, it is challenging to
488 map their rules within a unified framework for logical reasoning.
489 Meanwhile, many ML projects actually incorporate non-standard
490 licensing components, as mentioned in Section 1. If we consider
491 these claimed licenses to be invalid, then they would not pose any
492 license compliance issues. However, the validity of these licenses
493 depends on specific cases and the dispute resolution process by
494 the jurisdictional courts in accordance with the applicable laws in
495 different regions. As a license analyzer, we aim to maximize the
496 detection of all potential legal risks under various interpretations,
497 rather than merely granting a green light with low confidence. To
498 this end, we perform three generalizations to encode license rules.
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500 The first generalization is called *fuzz form matching*. We broaden
501 the definitions related to a work's form to encompass its general
502 form. For instance, we expand the license terms of GPL-3.0 concerning
503 source code to include all forms of work in the Raw categories,
504 such as model weights and corpus. In this way, we can extend the
505 scope of interpretation of GPL-3.0 to cover models and datasets.

506 The second generalization is called *composition-based rule alignment*,
507 which aims to resolve the pervasive ambiguities across different
508 licensing frameworks. This ambiguity often arises in non-standard
509 scenarios, for example, when licensing a model under
510 GPL-3.0, it may be unclear whether *Model Aggregation* (a technology
511 used in federated learning [21]) triggers the "Aggregate" clause
512 in GPL-3.0. Therefore, we propose a composition-based method to
513 align these rules. Specifically, we generalize the concept of action to
514 represent the compositional relationships between input and output.
515 For instance, the action *Combine* signifies that the input work
516 has been entirely included in the output work without modification.
517 This action corresponds to terms such as "Link" and "Aggregate" in
518 software licenses, "Collection" in CC licenses, and "MoE" in model
519 licenses. In the case of *Model Aggregation*, which produces an output
520 that contains parts of the input and is difficult to separate, it is not considered a *Combine*. Consequently, according to our rule
521 alignment, it will not activate the "Aggregate" clause in GPL-3.0.
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Figure 3: The Example of a Generalized GPL-3.0 Derivatives Rule in MG Analyzer.

The complete rule alignment method utilized in the MG Analyzer can be found in Table 1. It is worth mentioning that the meanings of these actions have been broadened and may differ from their original definitions. In some cases, multiple actions may align with the same license terms. For instance, the license term "Modify" can align with both the actions *Modify* and *Amalgamate*, as such licenses do not distinguish the extent of changes made or whether those changes can be reverted.

The final aspect is *applicable term generalization*, where we encode the triggering conditions of a license term into the following properties: range of input work forms, range of output work forms, and types of actions. Figure 3 illustrates an example of the GPL-3.0 derivatives rule³, which represents the *Combine* action applied to input works in code format, resulting in a code output. This action triggers the "derivative" clause in GPL-3.0, indicating that the license of the output work must be compatible with GPL-3.0 (e.g., APGL-3.0). Additionally, five restrictions must apply to the output work if it is to be republished, as dictated by this *definition dependency*. This rule does not include any *Use Restrictions*, which apply to output works regardless of whether they are republished. We found this subtle distinction to be crucial in ML license analysis, as most OSS license terms are triggered by distribution, and their definitions of "distribution" typically exclude publishing as a service. However, in the case of models, the common deployment method is through a web interface, leading to many OSS license restrictions being circumvented in such scenarios (ref Section 5).

Furthermore, multiple rules may lead to the same output definition, and we provide the option of *fuzz form matching* by enabling *fuzz rules* to enhance the interpretive capabilities of the MG Analyzer. It is worth mentioning that the reasoning results behind the restrictions derived from these rules require further analysis for validation. Taking the rule in Figure 3 as an example, the presence of additional discrimination terms in the final work that violate GNU freedom [12] dictates whether errors related to GNU freedom conflicts should be reported. We present snippets of our encoded rules written in Turtle format in Appendix B. The list of supported licenses, whose terms have been encoded in MG Analyzer, is shown in Table 3, covering nearly all top-ranking licenses for published models on HuggingFace⁴, a popular model publishing platform.

³ The original GPL-3.0 license text reads: "You may convey a work based on the Program ... in the form of source code ... provided that you also meet all of these conditions: ... stating that you modified it ... it is released under this License ... keep intact all notices ... license the entire work, as a whole, under this License ...".

⁴ <https://huggingface.co/models>

581 **Table 2: List of Notices, Warnings, and Errors Reported by**
 582 **MG Analyzer. The triggered work is denoted as ?work.**

Code	Report Type	Report Content
N1	Include License	The original license file from ?work should be retained.
N2	Include Notice	The notices (e.g., attribution, copyleft, patent, trademark) from ?work should be retained.
N3	State Changes	A notice stating the modifications made to ?work should be provided.
N4	ImpACT Reports	You need to complete a Derivative Impact Report.
W1	License Type Mismatch	Non-standard licensing of ?work.
W2	Revocable License	The license of ?work is revocable.
W3	Possibly Revocable License	The revocability of the license of ?work is not claimed.
W4	Right Not Granted	The required right is not explicitly granted by ?work.
W5	Disclose Source Code	This work should disclose its source code.
W6	Disclose Unmodified Code	The unmodified source code of ?work should be disclosed.
W7	Use Behavior	The use of this work must comply with the usage behavior restrictions of ?work.
W8	Runtime Control	There is a runtime restriction clause in ?work (e.g., forced updates).
E1	Wrong Work Type or Form	The type of ?work is inconsistent with its form.
E2	Right Reserved	The required right is reserved by the license of ?work.
E3	Not Allowed to Share	Redistribution of this work is prohibited.
E4	Not Allowed to Sublicense	Sublicensing of ?work is prohibited.
E5	Non-Commercial Use	Commercial use of ?work is prohibited.
E6	Cannot Be Relicensed	The license of this work is invalid because ?work cannot be relicensed, or relicensing is prohibited.
E7	GNU Freedom Conflict	The additional terms applied in this work may violate the GNU freedom clauses of ?work.
E8	CC Freedom Conflict	The additional terms applied in this work may violate the CC freedom clauses of ?work.
E9	Llama 2/3 Exclusive	Using Llama 2/3's output in non-Llama 2/3 derivatives is prohibited.
E10	Exclusive License	The additional terms applied in this work are prohibited by the license of ?work.

608 With MG Vocabulary, the ML workflow with compositional de-
 609 pendencies, and encoded license rules, we can reason to derive the
 610 definition and rights-using dependencies, thereby determining the
 611 applicable licenses for intermediate works. The license determina-
 612 tion in the MG Analyzer follows an incremental and minimal
 613 noncompliance strategy, where the new license only applies to the
 614 incremental parts of the work without affecting the original work
 615 (a common practice in licensing). Furthermore, to avoid introducing
 616 additional compliance issues during analysis, we use *Unlicense* as
 617 the default license when applicable. However, an exception arises
 618 with the license proliferation clauses found in copyleft licenses,
 619 such as GPL-3.0 and OSL-3.0, which require that the entire new
 620 work be licensed under the same terms. Our analyzer incorporates
 621 reasoning logic to identify applicable licensing solutions (a snippet
 622 of logic can be found in Appendix B), but unresolved conflicts may
 623 occur if multiple copyleft clauses are triggered. In such cases, the
 624 MG Analyzer will select one of these copyleft licenses and report
 625 an error during the *Analysis Stage*.

626 3.3 Compliance Analysis

627 At this stage, we establish all necessary dependency properties
 628 through automated reasoning to enable compliant license analy-
 629 sis. The analysis rules are designed to assess and report the valid-
 630 ity of the base workflow information, the fulfillment of granted
 631 rights, work restrictions, and overall license compliance. In addi-
 632 tion, the Publish action should be invoked to signify the completion
 633 of the workflow, along with an assigned public manner and work
 634 form. MG Analyzer considers three republication scenarios: in-
 635 ternal, share, and sell, each of which typically involves different
 636 terms and conditions in the licenses. For instance, if we publish
 637

638 the final work for sale, the related licenses should grant rights for
 639 redistribution, sublicensing, and commercial use.

640 Appendix B presents the logic code for rights granting analysis,
 641 and the full list of reported notices, warnings, and errors is shown
 642 in Table 2. Due to its staged logic rule reasoning design, MG Ana-
 643 lyzer has considerable extensibility, enabling the incorporation of
 644 additional licenses and analysis targets, provided that it can reason
 645 based on our proposed dependencies information. Beyond compli-
 646 ance analysis, our vision is to promote ML workflow supply chain
 647 management and improve FAIRness [45] in model publishing. We
 648 position our vocabulary and tool as a first step toward Linked Open
 649 Model Production Data [3].

650 4 MG Licenses

651 Although the MG Analyzer can identify potential non-compliance
 652 in existing ML projects, it does not offer an effective solution to
 653 prevent such issues in the future. To address this, we conducted
 654 a survey of the most widely used licenses for models published
 655 on HuggingFace and identified three major causes of license non-
 656 compliance in current ML projects: non-standard licensing, lack
 657 of general model licenses, and insufficiently defined licenses. The
 658 statistical results of a previous study [9] support part of our findings.

659 To reveal the underlying dilemmas in model licensing, we pro-
 660 vide comprehensive comparisons of these licenses in Table 3. Based
 661 on the terms of these licenses, we evaluated each license's clarity
 662 score and freedom score, each encompassing sub-items as defined
 663 in the table. A higher clarity score indicates that the license is more
 664 clearly defined in model publishing scenarios, while a higher free-
 665 dom⁵ score signifies fewer restrictions on republished copies and
 666 derivatives. The significant findings are summarized below:

667 ① **For OSS licenses**, most are not well defined in the context of
 668 model publishing, primarily due to the absence of clauses address-
 669 ing ML activities (Rules) and the lack of coverage for publishing as a
 670 service (Remote). This implies that mainstream model deployment
 671 practices, which often provide models as web services, are likely to
 672 circumvent the governance of these licenses. Additionally, commer-
 673 cial use and behavioral restrictions are not stipulated in most OSS
 674 licenses, which are common requirements in model publishing.

675 ② **For free-content and dataset licenses**, their average clarity
 676 score is only slightly better than that of OSS licenses, and they
 677 also lack coverage for publishing as a service. However, some CC
 678 licenses, such as CC-BY-NC-4.0, offer additional options that pro-
 679 hibit the commercial use of the work, unlike OSS licenses. This
 680 may explain why many models are published under these licenses⁶,
 681 despite the fact that they were not originally drafted for models.

682 ③ **For model licenses**, aside from the proposed MG licenses,
 683 most model licenses are not intended for general publishing pur-
 684 poses. For example, the terms in Llama 2 license is specifically
 685 drafted to govern the Llama 2 model and its derivatives⁷, failing to
 686 meet reusable standards. Additionally, since the purpose of these

687 ⁵ Our freedom score reflects only the amount of restrictions stipulated in a license and
 688 should not be confused with the definitions of freedom in free software [32].

689 ⁶ There are 9659 models on HuggingFace licensed under CC-BY-NC-4.0 (more than
 690 Llama 2), and 668 of them have garnered 1k+ downloads (accessed on October 8, 2024).

691 ⁷ For example, Clause 1.v. of the Llama 2 license reads: "You will not use the Llama
 692 Materials or any output or results of the Llama Materials to improve any other large
 693 language model (excluding Llama 2 or derivative works thereof)".

Table 3: List of MG Analyzer-Supported Licenses & Agreements (including MG Licenses) with Their Comparisons in Clarity and Freedom. Grouped by OSS, Free-Content (&Dataset), Model and sorted first by clarity score, then by freedom score.

License Name	Clarity of Definitions				Freedom of Verbatim Copy			Freedom of Derivative					Freedom of Use		Clarity	Freedom
	Prefixes	Rights	Rules	Remote	Share	Close	Non-excl.	Share	Close	Non-excl.	Sublicense	Attribute	Comm.	Behav.		
AGPL-3.0	✓	✓	≈	✓	✓	≈	✗	≈	✗	≈	✗	✗	✓	✓	3.5	4.5
APL-3.0	≈	✓	✓	≈	✓	≈	✓	✓	✓	≈	✓	✓	✓	✓	3.0	7.5
OSL-3.0	≈	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	3.0	5
Apache-2.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	7.5
LGPL-3.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	7.5
Artistic-2.0	≈	≈	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	6.0
GPL-3.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	4.5
ECL-2.0	≈	✓	✓	≈	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.0	7.5
Unlicensed	≈	≈	≈	≈	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	1.5	10
MIT	≈	≈	≈	≈	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	1.5	8.5
GPL-2.0	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	1.5	5.5
LGPL-2.1	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	1.5	5.5
BSD-3-Clause-Clear	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	1.0	7.5
BSD-2-Clause	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	1.0	7.5
WTPL1.2.0	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	0	10
CC0-1.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	3.0	10
ODC-By-1.0	≈	≈	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	3.0	7.5
PDDL-1.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	10
CC-BY-4.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	6.0
CC-BY-SA-4.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	6.0
CC-BY-NC-4.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	5.0
CC-BY-NC-SA-4.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	7.0
CC-BY-ND-4.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	4.0
CC-BY-NC-ND-4.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	3.0
GFDL	✓	≈	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.0	3.5
C-UDA	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	1.5	5.5
LGPLR	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	1.5	4.5
MG0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4.0	8.5
MG-BY	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4.0	7.5
MG-BY-RAI	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4.0	6.5
‡ OpenRAIL-M	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4.0	6.5
MG-BY-NC	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4.0	6.0
MG-BY-OS	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4.0	6.0
MG-BY-NC-RAI	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4.0	5.0
MG-BY-NC-OS	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4.0	4.5
MG-BY-ND	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4.0	3.5
MG-BY-NC-ND	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4.0	2.5
† OPT-175B	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	3.5	5.0
† Llama3	≈	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	5.5
† Llama3.1	≈	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.5	5.5
† A12-ImpACT-LR	≈	✗	✓	✓	✓	✓	✓	n/a	n/a	✓	✓	✓	✓	✓	2.5	5.5
† A12-ImpACT-MR	≈	✗	✓	✓	✓	✓	✓	n/a	n/a	✓	✓	✓	✓	✓	2.5	0
† A12-ImpACT-HR	≈	✗	✓	✓	✓	✓	✓	n/a	n/a	✓	✓	✓	✓	✓	2.5	0
† Gemma2	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2.0	4.5
† Llama2	≈	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	1.5	5.5

Header Definitions:

Prefixes: ✓ The license explicitly includes sufficient prefixes that clearly describe scope and conditions of granting rights (e.g., revocable, sublicensable); ≈ Some important prefixes are indeterminate; ✗ No prefixes are declared.

Rights: ✓ The license explicitly declares whether a patent license or a copyright license is granted; ≈ Only the granting of a patent license or copyright license is stated; ✗ No explicit grant of either is provided.

Rules: ✓ The license terms cover all actions listed in Table 1; ≈ Some actions fall outside the definition of this license; ✗ Almost no rules are set forth.

Remote: ✓ The license considers remote access situations (e.g., via API, Web, SaaS); ≈ No definitions or rules regarding remote access behaviors are set forth.

Share: ✓ The license permits the sharing of verbatim copies/derivatives created by you without any restrictions; ≈ Some restrictions apply to sharing; ✗ Sharing verbatim copies/derivatives is prohibited.

Close: ✓ The license does not require you to disclose the source files of verbatim copies/derivatives created by you; ≈ Modification statements are required; ✗ You must disclose the source files of your created copies/derivatives.

Non-exclusive: ✓ The license does not restrict you from adding new terms when republishing; ≈ Certain types of terms are prohibited in republishing; ✗ All republishing must adhere to the original terms and conditions.

Sublicense: ✓ The license explicitly grants sublicensing rights; ≈ The license prohibits sublicensing but offers automatic licensing instead; ✗ Sublicensing is either prohibited or not explicitly permitted.

Attribute: ✓ The license does not require retaining the original attribution and licenses in redistributed derivatives; ≈ Attribution of license must be retained; ✗ Redistributed derivatives must retain the attributions and licenses.

Commercial: ✓ The license explicitly grants commercial rights; ≈ Commercial rights are not explicitly granted but not reserved either, or compromised commercial rights are granted; ✗ Commercial rights are reserved.

Behavioral: ✓ The license does not restrict user behaviors; ≈ Includes runtime controls (e.g., forced updates); ✗ Certain behaviors involving the licensed materials or derivatives are prohibited (e.g., harming, medical advice).

Clarity/Freedom Score: ✓ +1.0, ≈ +0.5, ✗ n/a + 0. Maximum Clarity Score: 4.0, Maximum Freedom Score: 10.

Explanations:

* Although CC0-1.0 explicitly states that sublicensing is not allowed, sublicensing becomes unnecessary due to the Waiver of Rights.

** Since CC-BY-ND-4.0 and CC-BY-NC-ND-4.0 prohibit the sharing of derivatives, judgments regarding redistributed derivatives are marked as "n/a" in the table.

† These licenses (or terms of use, or agreements) are specifically drafted for certain products and are not intended for general model publishing purposes.

‡ As there are no fundamental differences between CreativeML Open RAIL-M, OpenRAIL++M, BigCode Open RAIL-M, and BigScience Open RAIL-M, these licenses are grouped under OpenRAIL-M.

• We have used an archive of the A12-ImpACT license; the version is 2.0, with an effective date of January 8, 2024.

publishing scenarios. The options include: BY (Attribution), NC (Non-Commercial), ND (No Derivatives), RAI (Responsible Use of AI), and OS (Open Source)⁹. We drafted nine preset licenses using these options, including MG0, which does not apply any options. The flexibility of our licenses is reflected in table 3, where their freedom scores are evenly distributed between 3.5 and 8.5, indicating that they form a superset of all other model licenses¹⁰. To promote transparency, we introduced a *Model Sheet* as an attachment to each MG License, inspired by MDL [2]. This sheet assists model users in understanding the rights and restrictions granted by the license

⁹ At the time of writing, the Open Source Initiative has only released a draft v. 0.0.9 version of the Open Source AI definition, and our MG licenses with the OS option are not OSI-approved at present.

¹⁰ A12-ImpACT-MR and A12-ImpACT-HR prohibit sharing copies, we do not consider such restrictions to be common in model publishing, so we have excluded them. For further details, refer to Figure 6 in Appendix C.

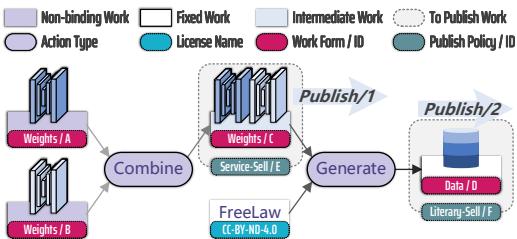


Figure 4: Example Workflow: Combine Models, Then Publish.

Table 4: Settings and Analysis Results from MG Analyzer with Fuzz Form Matching Enabled.

Work: License	Work: Report code
(i) C: AGPL-3.0. D: Unlicense.	(i) E: N1N2N3×2; W5×2; W1×3. F: W1×3.
(ii) D: Unlicense	(ii) E: W1×2. F: W1.
OSS License Setting:	
(i) A←PhoBERT [28]: AGPL-3.0. B←CKIP-Transformers [23]: GPL-3.0.	
(ii) A←PhoBERT [28]: AGPL-3.0. B←None.	
C: Unlicense. D: Unlicense.	E: W1×2; E2×2; E5×2. F: W1×2.
Free-content License Setting:	
A← MPT-Chat [41]: CC-BY-NC-SA-4.0. B←Command R+ [4]: CC-BY-NC-4.0.	
(iii) D: Unlicense.	(iii) E: N1; N2; W5 . F: None.
(iv) D: Unlicense.	(iv) E: N1; N2; W2×2; E2; E5. F: W2, E5.
Model License Setting:	
(iii) A← MG-BY-OS. B←None. (iv) A← MG-BY-NC. B←None.	

terms and helps model developers identify the most suitable license for their needs (ref Appendix C).

In the next section, we explore which licenses can protect your model from misuse beyond your intended purposes. For example, licensee may close source your GPL-licensed model without violating your license, even if it does contain code disclosure clauses. To do this, we evaluate some of the popular licenses for model publishing, as well as the MG Licenses, using MG Analyzer.

5 Experiments

This section seeks to answer a key question: *Should I continue using traditional OSS and free-content licenses to publish my model, and what are the associated risks?* To explore this question, we evaluate commonly adopted licenses in the context of model publishing by MG Analyzer to assess whether they are still effective as intended. The example workflow involves combining two models and publishing them as a service, as shown in Figure 4. Here, we consider two scenarios: 1) publishing the combined model as a service; 2) publishing the data generated from the combined model. Models A and B are non-binding works that correspond to the settings in Table 4, with their respective analysis results also presented in the table. Model C is an intermediate work created by combining A and B, and Data D is the generated output from C. Work E involves republishing C as a service with the intent to sell, while Work F involves republishing D as a literary form, also with the intent to sell. To be more convincing, we use real-world models and their respective licenses for demonstration.

First, we evaluate two OSS licenses: AGPL-3.0 and GPL-3.0, which are considered enforceable open-source licenses with copyleft clauses. In setting (i), Work E triggers two *Disclose Source Code*

warnings (code W5, refer to Table 2 for code definitions), and AGPL-3.0 successfully proliferates¹¹ to Work C. However, with a small adjustment, we can circumvent these clauses by republishing the generated content rather than providing the model as a service. As demonstrated by Work D, there is no W5 warning, and the content is licensed under the Unlicense. Furthermore, the condition in AGPL-3.0 that triggers the disclose code clauses related to remote access is *you modify the Program*, which means you can directly republish copies as a service to circumvent this clause. As reflected in setting (ii), there are no more W5 warnings, only two warnings related to the non-standard licensing remain.

Second, we evaluate two free-content licenses: CC-BY-NC-SA-4.0 and CC-BY-NC-4.0, both of which prohibit the commercial use of the governed work. As shown in the results, the republication of Work E successfully triggers E2 errors because the rights to commercial use are reserved. However, we can still circumvent these clauses by generating and then sharing the output, as these licenses lack rules regarding the generated work.

Third, we evaluate MG Licenses: MG-BY-OS and MG-BY-NC, which contain open sourcing and non-commercial use clauses, respectively. In setting (iii), our MG-BY-OS license successfully triggers the W5 warning, indicating that Work E must disclose its source code. In setting (iv), the non-commercial use error E5 is reported by the generated Work F. As a model license, we do not enforce licensing on generated content, allowing Work D to be licensed under the Unlicense, albeit with certain restrictions. A summary of the rights granted and restrictions imposed by these licenses can be found in their *Model Sheet* provided in Appendix C.

It is worth mentioning that all results were obtained with *fuzzy form matching* enabled, maximizing the detection of potential risks. If these *fuzz rules* were disabled, fewer issues would be reported. Furthermore, our MG Analyzer is designed to help developers be aware of potential compliance issues in ML projects. Its results should not be considered legal advice or a defense in dispute resolution. Please refer to our disclaimers in Appendix A.

Summary: GPL, AGPL, and CC licenses can be easily circumvented, leading to unintended misuse of the ML models they govern. In contrast, MG Licenses offer greater clarity and flexibility tailored to various publishing scenarios, promoting a more standardized and transparent approach to model licensing.

6 Conclusion

Non-standard licensing is prevalent in ML projects, and the underlying risks are often neglected. To reveal these risks, we propose formal ontologies for describing ML workflows and develop the MG Analyzer to detect compliance issues based on it. To promote more standardized licensing in the future, we have drafted MG Licenses to provide flexible licensing solutions for model publishing. Our experiments show that commonly used OSS and CC licenses are unsuitable for model publishing, while MG Licenses provide a viable alternative.

¹¹While two copyleft conditions are simultaneously triggered here, they can be resolved because GPL-3.0 is compatible with AGPL-3.0. Appendix D visualizes this workflow.

References

- [1] Dörthe Arndt and Stephan Mennicke. 2023. Notation3 as an existential rule language. In *International Joint Conference on Rules and Reasoning (RuleML+RR)*. Springer, 70–85. https://doi.org/10.1007/978-3-031-45072-3_5
- [2] Misha Benjamin, Paul Gagnon, Negar Rostamzadeh, Chris Pal, Yoshua Bengio, and Alex Shee. 2019. Towards standardization of data licenses: The montreal data license. *arXiv preprint arXiv:1903.12262* (2019).
- [3] Christian Bizer, Tom Heath, Kingsley Idehen, and Tim Berners-Lee. 2008. Linked data on the web (LDOW2008). In *Proceedings of the 17th international conference on World Wide Web (WWW)*. 1265–1266. <https://doi.org/10.1145/1367497.1367760>
- [4] CohereForAI. 2024. C4AI Command R+. Retrieved October 1, 2024 from <https://huggingface.co/CohereForAI/c4ai-command-r-plus>
- [5] Creative Commons. 2024. Creative Commons Licenses List. Retrieved October 1, 2024 from <https://creativecommons.org/licenses/>
- [6] Danish Contractor, Daniel McDuff, Julia Katherine Haines, Jenny Lee, Christopher Hines, Brent Hecht, Nicholas Vincent, and Hanlin Li. 2022. Behavioral use licensing for responsible AI. In *2022 ACM Conference on Fairness, Accountability, and Transparency (FAccT)*. 778–788. <https://doi.org/10.1145/3531146.3533143>
- [7] Xing Cui, Jingzheng Wu, Yanjun Wu, Xu Wang, Tianyue Luo, Sheng Qu, Xiang Ling, and Mutian Yang. 2023. An Empirical Study of License Conflict in Free and Open Source Software. In *2023 IEEE/ACM 45th International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP)*. IEEE, 495–505. <https://doi.org/10.1109/ICSE-SEIP58684.2023.00050>
- [8] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 17th Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*. 4171–4186. <https://doi.org/10.18653/v1/n19-1423>
- [9] Moming Duan, Qinbin Li, and Bingsheng He. 2024. ModelGo: A Practical Tool for Machine Learning License Analysis. In *Proceedings of the ACM on Web Conference 2024 (WWW)*. 1158–1169. <https://doi.org/10.1145/3589334.3645520>
- [10] Linux Foundation. 2024. SPDX License List. Retrieved October 1, 2024 from <https://spdx.org/licenses/>
- [11] Tommaso Furlanello, Zachary Lipton, Michael Tschannen, Laurent Itti, and Anima Anandkumar. 2018. Born again neural networks. In *Proceedings of the 35th International Conference on Machine Learning (ICML)*. PMLR, 1607–1616.
- [12] Eli Greenbaum. 2016. The Non-Discrimination Principle in Open Source Licensing. *Cardozo Law Review* 37, 4 (2016), 1297–1344.
- [13] Dirk Groeneveld, Iz Beltagy, Pete Walsh, Akshita Bhagia, Rodney Kinney, Oyvind Tafjord, Ananya Harsh Jha, Hamish Ivison, Ian Magnusson, Yizhong Wang, et al. 2024. OLMo: Accelerating the science of language models. *arXiv preprint arXiv:2402.00838* (2024).
- [14] Edward J Hu, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. 2022. LoRA: Low-Rank Adaptation of Large Language Models. In *International Conference on Learning Representations (ICLR)*.
- [15] Eero Hyvönen, Jouni Tuominen, Miika Alonen, and Eetu Mäkelä. 2014. Linked Data Finland: A 7-star model and platform for publishing and re-using linked datasets. In *The Semantic Web: ESWC 2014 Satellite Events: ESWC 2014 Satellite Events, Anissaras, Crete, Greece, May 25–29, 2014, Revised Selected Papers 11*. Springer, 226–230. https://doi.org/10.1007/978-3-319-11955-7_24
- [16] Black Duck Software Inc. 2024. Black Duck Software Composition Analysis. Retrieved October 1, 2024 from <https://www.blackduck.com/software-composition-analysis-tools/black-duck-sca.html>
- [17] Michael C Jaeger, Oliver Fendt, Robert Gobeille, Maximilian Huber, Johannes Najjar, Kate Stewart, Steffen Weber, and Andreas Wurl. 2017. The FOSSology project: 10 years of license scanning. *International Free and Open Source Software Law Review* 9 (2017), 9.
- [18] Wenxin Jiang, Nicholas Synovic, Matt Hyatt, Taylor R Schorlemmer, Rohan Sethi, Yung-Hsiang Lu, George K Thiruvathukal, and James C Davis. 2023. An empirical study of pre-trained model reuse in the hugging face deep learning model registry. In *Proceedings of the 45th IEEE/ACM International Conference on Software Engineering (ICSE)*. 2463–2475. <https://doi.org/10.1109/ICSE48619.2023.00206>
- [19] Daniel Krech, Gunnar Astrand Grimnes, Graham Higgins, Jörn Hees, Iwan Aucamp, Niklas Lindström, Natanael Arndt, Ashley Sommer, Edmond Chuc, Ivan Herman, Alex Nelson, Jamie McCusker, Tom Gillespie, Thomas Kluyver, Florian Ludwig, Pierre-Antoine Champin, Mark Watts, Urs Holzer, Ed Summers, Whit Morriss, Donny Winston, Drew Pertula, Filip Kovacevic, Remi Chateauneuf, Harold Solbrig, Benjamin Cogrel, and Veyndan Stuart. 2023. RDFLib. <https://doi.org/10.5281/zenodo.6845245>
- [20] Dengchun Li, Yingzi Ma, Naizheng Wang, Zhiyuan Cheng, Lei Duan, Jie Zuo, Cal Yang, and Mingjie Tang. 2024. MixLoRa: Enhancing large language models fine-tuning with lora based mixture of experts. *arXiv preprint arXiv:2404.15159* (2024).
- [21] Qinbin Li, Bingsheng He, and Dawn Song. 2021. Model-contrastive federated learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 10713–10722.
- [22] Andreas Liesenfeld and Mark Dingemanse. 2024. Rethinking open source generative AI: open washing and the EU AI Act. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*. 1774–1787. <https://doi.org/10.1145/3630106.3659005>
- [23] Chin-Tung Lin and Wei-Yun Ma. 2022. HanTrans: An Empirical Study on Cross-Era Transferability of Chinese Pre-trained Language Model. In *Proceedings of the 34th Conference on Computational Linguistics and Speech Processing (ROCLING 2022)*. 164–173.
- [24] Google LLC. 2024. Gemma Terms of Use. Retrieved October 1, 2024 from <https://ai.google.dev/gemma/terms>
- [25] Nestor Maslej, Loredana Fattorini, Raymond Perrault, Vanessa Parli, Anka Reuel, Erik Brynjolfsson, John Etchemendy, Katrina Ligett, Terah Lyons, James Manyika, Juan Carlos Niebles, Yoav Shoham, Russell Wald, and Jack Clark. 2024. *The AI Index 2024 Annual Report*. Stanford University, Stanford, CA.
- [26] Arunesh Mathur, Harshal Choudhary, Priyank Vashist, William Thies, and Santhi Thilagam. 2012. An empirical study of license violations in open source projects. In *2012 35th Annual IEEE Software Engineering Workshop (SEW)*. IEEE, 168–176. <https://doi.org/10.1109/SEW.2012.24>
- [27] Inc. Meta Platforms. 2024. Llama 2 Community License. Retrieved October 1, 2024 from <https://ai.meta.com/llama/license/>
- [28] Dat Quoc Nguyen and Anh Tuan Nguyen. 2020. PhoBERT: Pre-trained language models for Vietnamese. In *Findings of the Association for Computational Linguistics: EMNLP 2020*. 1037–1042. <https://doi.org/10.18653/v1/2020.findings-emnlp.92>
- [29] Bolin Ni, Houwei Peng, Minghao Chen, Songyang Zhang, Gaofeng Meng, Jianlong Fu, Shiming Xiang, and Haibin Ling. 2022. Expanding language-image pre-trained models for general video recognition. In *European Conference on Computer Vision (ECCV)*. Springer, 1–18. https://doi.org/10.1007/978-3-031-19772-7_1
- [30] Philippe Ombedanne. 2020. Free and open source software license compliance: tools for software composition analysis. *Computer* 53, 10 (2020), 105–109. <https://doi.org/10.1109/MC.2020.3011082>
- [31] Jeff Z Pan. 2009. *Resource description framework*. Springer, 71–90. https://doi.org/10.1007/978-3-540-92673-3_3
- [32] Bruce Perens. 1999. The open source definition. *Open sources: voices from the open source revolution* 1 (1999), 171–188.
- [33] Midjourney platform. 2024. Midjourney's Terms of Service. Retrieved October 1, 2024 from <https://docs.midjourney.com/docs/terms-of-service>
- [34] PromptHero. 2024. Openjourney v4. Retrieved October 1, 2024 from <https://www.openjourney.art/>
- [35] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog* 1, 8 (2019), 9.
- [36] Gopi Krishnan Rajbahadur, Erika Tuck, Li Zi, Dayi Lin, Boyuan Chen, Zhen Ming, Daniel M German, et al. 2021. Can I use this publicly available dataset to build commercial AI software?—A Case Study on Publicly Available Image Datasets. *arXiv preprint arXiv:2111.02374* (2021).
- [37] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. 2022. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 10684–10695. <https://doi.org/10.1109/CVPR52688.2022.01042>
- [38] Lawrence Rosen. 2005. *Open Source Licensing: Software Freedom and Intellectual Property Law*. Prentice Hall Professional Technical Reference, New Jersey.
- [39] Hendrik Schoettl. 2019. Open source license compliance—why and how? *Computer* 52, 8 (2019), 63–67. <https://doi.org/10.1109/MC.2019.2915690>
- [40] Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B Hashimoto. 2023. Alpaca: A strong, repliable instruction-following model. *Stanford Center for Research on Foundation Models*. <https://cfrm.stanford.edu/2023/03/13/alpaca.html> 3, 6 (2023), 7.
- [41] MosaicML NLP Team. 2023. *Introducing MPT-7B: A New Standard for Open-Source, Commercially Usable LLMs*. www.mosaicml.com/blog/mpt-7b Accessed: 2025-10-01.
- [42] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasminne Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288* (2023).
- [43] Ruben Verborgh and Jos De Roe. 2015. Drawing conclusions from linked data on the web: The EYE reasoner. *IEEE Software* 32, 3 (2015), 23–27.
- [44] Jason Wei, Najoung Kim, Yi Tay, and Quoc Le. 2023. Inverse Scaling Can Become U-Shaped. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 15580–15591. <https://doi.org/10.18653/v1/2023.emnlp-main.963>
- [45] Mark D Wilkinson, Michel Dumontier, Ijsbrand Jan Aalbersberg, Gabrielle Appleton, Myles Axton, Aria Baak, Niklas Blomberg, Jan-Willem Boiten, Luiz Bonino da Silva Santos, Philip E Bourne, et al. 2016. The FAIR Guiding Principles for scientific data management and stewardship. *Scientific data* 3, 1 (2016), 1–9. <https://doi.org/10.1038/sdata.2016.18>
- [46] Shan You, Chang Xu, Fei Wang, and Changshui Zhang. 2021. Workshop on Model Mining. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. 4177–4178. <https://doi.org/10.1145/3447548.3469471>

1045 A Disclaimers

1046 The information in this article is for general informational purposes
 1047 only and does not constitute legal advice. Views, opinions, and
 1048 recommendations expressed are solely those of the author(s) and
 1049 do not represent any organization. Do not rely on this material as
 1050 a substitute for professional legal advice tailored to your specific
 1051 circumstances.

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B Encoded Rules and Reasoning Logic

In this section, we present the encoded "derivative" rules for the GPL-3.0 and Llama 2 licenses in Turtle format, followed by a snippet of the reasoning logic employed for license determination and rights granting analysis in Notation3.

MGLicenseRule.ttl > GPL-3.0-derivative-rule-1

```

@prefix mg: <http://~/rdf/terms#> .
mg:GPL-3.0-derivative-rule-1 a mg:Rule ;
  mg:hasOutputDef mg:derivative ;
  mg:targetActionType mg:Combine ;
  mg:targetInputWorkForm mg:code ;
  mg:targetOutputWorkForm mg:code ;
  mg:relicense mg:compatible-license ;
  mg:hasPublishRestriction mg:include_license_restriction,
    mg:include_notice_restriction, mg:disclose_self_restriction,
    mg:state_changes_restriction, mg:gnu_freedom_restriction ;
  mg:allowSharing true .

```

MGLicenseRule.ttl > Llama2-derivative-rule

```

@prefix mg: <http://~/rdf/terms#> .
mg:Llama2-derivative-rule a mg:Rule ;
  mg:hasOutputDef mg:derivative ;
  mg:targetActionType mg:Amalgamate, mg:Combine,
    mg:Modify, mg:Train, mg:Embed, mg:Distill ;
  mg:targetInputWorkForm mg:weights, mg:exe ;
  mg:targetOutputWorkForm mg:weights, mg:exe ;
  mg:relicense mg:any-license ;
  mg:hasPublishRestriction mg:include_license_restriction ;
  mg:hasUseRestriction mg:llama2_exclusive_use_restriction,
    mg:use_behavior_restriction ;
  mg:allowSharing true .

```

ruling.n3 > License Determination Logic (snippet)

```

@prefix log: <http://www.w3.org/2000/10/swap/log#> .
@prefix list: <http://www.w3.org/2000/10/swap/list#> .
@prefix mg: <http://~/rdf/terms#> .
{ # CASE-3: There have multiple rulings require the output work's license
  # should be compatible, and a compatible solution exists.
  ?outw a mg:Work .
  -x log:notIncludes { ?outw mg:hasLicense ?li } .
  # If all relied works have a license, we can determine the license of this work.
  {?outw mg:hasReliedwork ?relw} {?relw mg:hasLicense ?li} log:forAllIn _:t .
  # There is no ruling that NOT allow relicensing (For exclude CASE-2).
  {?outw!mg:hasRuling!mg:hasRule mg:relicense ?reli }
  {?reli log:notEqualTo mg:none-license} log:forAllIn _:t .
  # Collect all compatible-relicensable licenses into a list.
  (?li
  {
    ?outw mg:hasRuling ?rlng .
    ?rlng!mg:hasRule mg:relicense ?rule .
    ?rule log:equalTo mg:compatible-license . # Compatible
    ?rlng mg:hasLicense ?li .
    ?li mg:hasCompatibleLicense ?clist.
  }
  ?li_list ) log:collectAllIn _:t . # (CASE-1 will yield an empty list here) .
  ?li_list list:first ?li_1st .
  ?li_1st mg:hasCompatibleLicense ?compat_list_1st .
  -x log:includes { ?cli list:in ?compat_list_1st .
  {?li_list!list:member mg:hasCompatibleLicense ?compat_list_other}
  {?cli list:in ?compat_list_other} } log:forAllIn _:t . } .
} => {
  ?outw mg:hasLicense ?li_1st .
} .

```

analysis_granting.n3 > Right Reserved Error

```

{ # Error [Right Reserved]. License reserves the right for your action.
?req a mg:Request .
?req!mg:grant mg:hasUsage ?req_usage . # There may be multiple mg:Usage.
?req mg:targetAction ?a .
?req mg:targetWork ?outw .
?req <- mg:hasRequest ?inw .
?inw mg:hasLicense ?li . # The checking target work must have a license.
# Collect all reserved rights according to the license.
( ?r { ?li!mg:reserve mg:hasUsage ?r . } ?reserved_list ) log:collectAllIn _:x .
?req_usage list:in ?reserved_list .
(?a ?inw ?outw ?req_usage) log:skolem ?geniri . # Keep unique
"**_Error_*-[Right Reserved]_*" ?req_usage "is_reserved_by" ?li "license_for"
?a "action_on" ?inw "to_produce" ?outw string:concatenation ?content .
} => {
  ?geniri a mg:Error ;
  mg:reportBy ?a ;
  mg:reportType "Right Reserved" ;
  mg:content ?content .
} .

```

C Supplementary of MG Licenses

Table 5 and Table 6 present the *Model Sheet* included in the Attachment of our proposed MG Licenses. For instance, the *Model Sheet* for MG-BY-NC indicates that this license is revocable, prohibits commercial use of the model, its output, associated code, documentation, and derivatives, and does not require disclosure of source weights or impose responsible AI restrictions. In comparison, MG-BY-OS has fewer restrictions, with its primary requirement being the disclosure of model weights.

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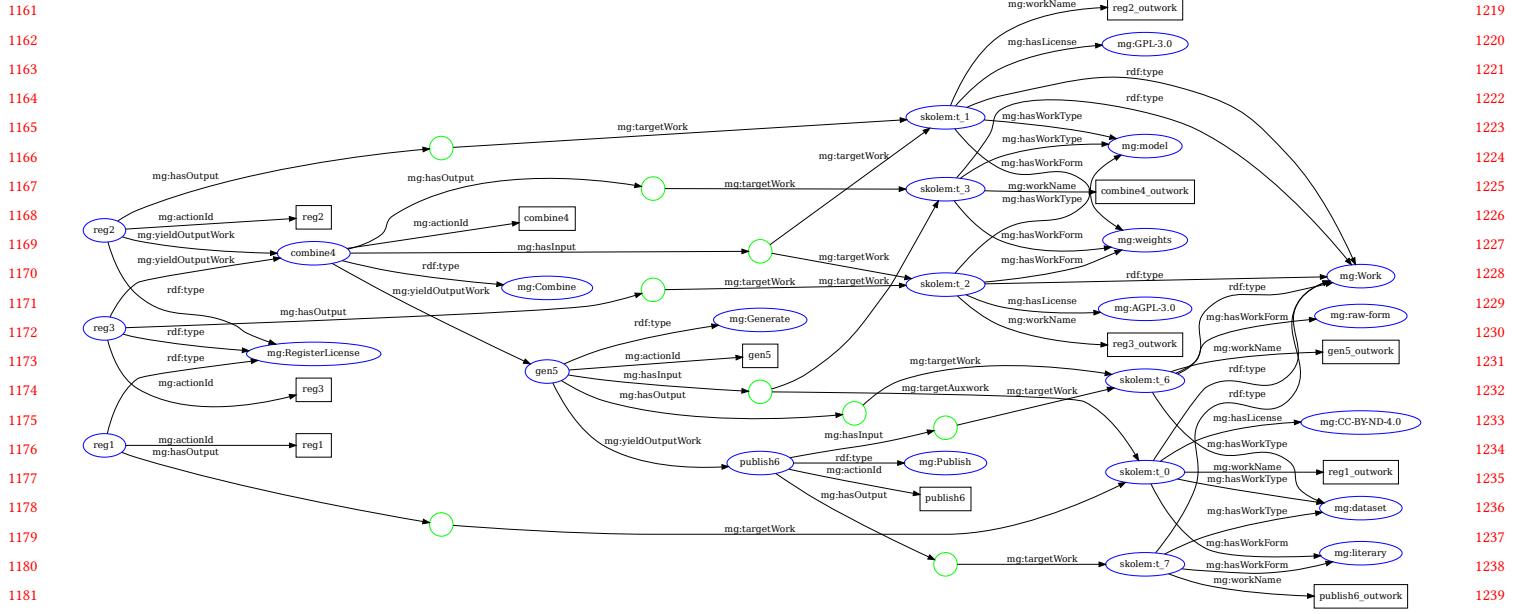


Figure 5: RDF Graph Visualization of the OSS Licenses Example Workflow in Section 5, Setting (i).

Table 5: Model Sheet of MG-BY-NC.

Use & Modify	✓	Sublicensing	✗
Create Derivatives	✓	Irrevocable	✗
Share Verbatim Copy	✓	Trademark Use	✗
Share Derivatives	✓	Commercial Use of Model	✗
Share Output	✓	Commercial Use of Output	✗
Patent Use	✓	Commercial Use of Derivatives	✗
Copyright Use	✓	Commercial Use of Code & Docs	✗
Retain Original Attribution	✓	Disclose Source	✗
Retain Original License	✓	Responsible AI Restrictions	✗
Retain All Notices	✓		
Disclaimer of Warranty	✓		
Limitation of Liability	✓		

Table 6: Model Sheet of MG-BY-OS.

Use & Modify	✓	Trademark Use	✗
Create Derivatives	✓	Responsible AI Restrictions	✗
Share Verbatim Copy	✓		
Share Derivatives	✓		
Share Output	✓		
Patent Use	✓		
Copyright Use	✓		
Commercial Use of Model	✓		
Commercial Use of Output	✓		
Commercial Use of Derivatives	✓		
Commercial Use of Code & Docs	✓		
Retain Original Attribution	✓		
Retain Original License	✓		

Figure 6 shows the coverage of MG Licenses. MG Licenses can serve as a substitute for all other model licenses in general model publishing purposes. In particular, the MG-BY-RAI license can substitute for OpenRAIL-M; the MG-BY-NC-RAI license can be seen as a substitute for Llama 2/3/3.1, OPT-175B, and AI2-ImpACT-LR

licenses; and the MG-BY-OS license can nearly substitute for the Gemma license in general model publishing scenarios.

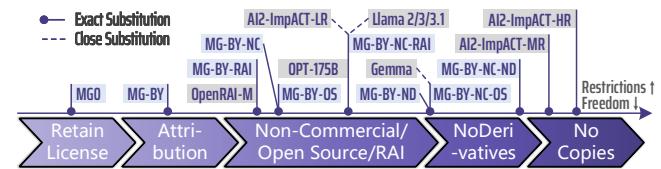


Figure 6: The Coverage of Model Publishing Scenarios by MG Licenses.

D RDF Workflow Visualization

Figure 5 illustrates the visualization of the workflow constructed by the MG Analyzer, as presented in the OSS licenses example in Section 5, Setting (i), which involves the publishing of Data D. This figure was generated using RDF Grapher, provided by the Linked Data Finland platform [15].