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# THE MODEL OPENNESS FRAMEWORK: PROMOTING COMPLETENESS AND OPENNESS FOR REPRODUCIBILITY, TRANSPARENCY, AND USABILITY IN ARTIFICIAL INTELLIGENCE

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## ABSTRACT

Generative AI (GAI) offers unprecedented opportunities for research and innovation, but its commercialization has raised concerns about transparency, reproducibility, and safety. Many open GAI models lack the necessary components for full understanding and reproducibility, and some use restrictive licenses whilst claiming to be “open-source”. To address these concerns, we propose the Model Openness Framework (MOF), a ranked classification system that rates machine learning models based on their completeness and openness, following principles of open science, open source, open data, and open access. The MOF requires specific components of the model development lifecycle to be included and released under appropriate open licenses. This framework aims to prevent misrepresentation of models claiming to be open, guide researchers and developers in providing all model components under permissive licenses, and help individuals and organizations identify models that can be safely adopted without restrictions. By promoting transparency and reproducibility, the MOF combats “openwashing” practices and establishes completeness and openness as primary criteria alongside the core tenets of responsible AI. Wide adoption of the MOF will foster a more open AI ecosystem, benefiting research, innovation, and adoption of state-of-the-art models.

**Keywords** Artificial intelligence · machine learning · open science · open source software · open data

## 1 Introduction

Artificial intelligence (AI) has seen remarkable advances in recent years [1], driven by the growth in computational capabilities [2, 3], available training data [4, 5], and improved deep learning algorithms [6, 7, 8]. However, as AI systems have become more advanced, concerns have also grown regarding their transparency, reproducibility, and safety [9, 10, 11]. Most state-of-the-art (SOTA) models are black boxes, making it hard to explain their internal logic or to ensure fairness [12, 13]. While the number of publicly available models has been growing, many of

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these models are falsely being promoted as “open-source”, a practice that has been characterized as “openwashing” [14, 15, 16, 17, 18]. The lack of transparency and reproducibility in AI models hinders scientific progress and erodes trust in AI research and development (R&D) [19, 20]. Without a standardized framework to evaluate and promote openness, it becomes challenging to verify claims, build upon existing work, and ensure responsible development.

To address these concerns, we introduce the Model Openness Framework (MOF) for evaluating and classifying the completeness and openness of machine learning (ML) models across their development process. Model producers must go beyond releasing models and trained weights; they should include all artifacts involved in the model development lifecycle. The MOF contributes to broader efforts that seek to promote transparency, reproducibility, and responsibility in AI R&D, including reproducibility checklists [20], ethical AI guidelines [21], model and data cards [22, 23]. By adopting the MOF, the AI community can create a more open, accountable, and trustworthy ecosystem.

For the sake of simplicity in nomenclature, this paper refers to any person or entity that develops and trains a first-generation model as a “model producer” or simply a “producer”. This encompasses AI researchers, developers, AI hobbyists, or anyone who trains a model in some form or fashion, including fine-tuning and alignment, as long as they are the originator of the (foundation) model. Similarly, any person or entity that adopts, consumes, alters, or uses a model and corresponding artifacts for any purpose including modifying weights through fine-tuning is referred to as a “model consumer” or simply a “consumer”. This includes end users, researchers, developers, or anyone that uses an ML model and is not its producer. We also use the terms “ML” and “ML model” to broadly describe any model, whether classical machine learning or deep learning and both generative and discriminative.

The paper has the following structure. It begins with a discussion of related work and how the MOF builds on prior approaches to evaluating the openness of models (Section 2). Next, it reviews the concepts of openness and completeness in science and technology (Section 3). Then, it introduces the MOF’s components (Section 4), acceptable licenses for each component (Section 6), and the three MOF classes (Section 5). Then, it discusses how to implement the framework in practice (Section 7), as well as the benefits (Section 8) and limitations (Section 9) of the MOF for promoting openness in AI R&D. Finally, it concludes with a summary of the key contributions of the MOF (Section 10).

## 2 Related Work

### 2.1 Opening the Black Box: Benefits & Risks of Openness in AI

AI has seen remarkable advances in recent years [1], driven by growth in computational capabilities [2, 3], increased volumes of training data [4, 5], and improved deep learning algorithms [6], such as transformers [8] and diffusion models [7]. However, most SOTA foundation models are black boxes, making it hard to explain their logic or behavior [12, 13]. What is more, large (language) model services like OpenAI’s GPT-4 hide opaque models behind cloud-based APIs, providing no insight into the inner workings [24]. To address these concerns, there has been a growing movement towards the openness of models with companies, research organizations, and individuals sharing models on platforms like Hugging Face Hub, GitHub, and Kaggle [25, 26, 27]. Furthermore, grassroots initiatives have emerged as the early leaders in the open development of open foundation models [28, 29], such as GPT-Neo by EleutherAI [30], BLOOM by BigScience [31], and SantaCoder by BigCode [32]. This shift towards the open development and availability of models is increasingly viewed as a credible alternative to closed-source development of AI [33].

There has been much debate about the benefits and risks of releasing models [34, 35, 36, 37, 38, 39]. On the one hand, the accessibility and transparency of open models can concurrently deliver advantages over closed source models, including security and performance advantages through distributed development and auditing [40, 41], adaptability and customization for diverse domains and languages [36, 42], as well as advances in science [43, 44, 45]. On the other hand, the openness of models introduces a number of risks, such as the generation of disinformation [46, 47], illegal content [48], as well as security vulnerabilities [49]. Open foundational models are understood to have five distinctive properties that present *both* benefits and risks: broader access, greater customizability, local adaptation and inference ability, the inability to rescind model access, and the inability to monitor or moderate model usage [36]. A systematic review of benefits and risks in the short, medium, and long terms concludes that the benefits outweigh the costs and accordingly encourages the open sourcing of models as well as training and evaluation data [39]. Striking a balance between the benefits and associated risks of open models remains a critical challenge in the AI R&D landscape.

### 2.2 Lack of Openness in “Open Source” AI

Publicly-available models are being falsely promoted as “open-source” [15, 16, 17, 18]. While there is a fast-growing number of open models and open datasets shared on online platforms, a concerning number of models and datasets are shared either without licenses—for example, 64.67% of models and 72.13% of datasets on Hugging Face Hub are unlicensed [27]—or with restrictive licenses that do not meet the standards required of open licenses [15, 16]. Some

model producers even add conditions that stipulate that their model outputs cannot be used to train subsequent models or add trigger conditions that would require a model consumer to negotiate a new license when some condition is met. In addition, fine-tuned models based on foundation models with restrictive licenses are being released with open-source licenses, such as Apache 2.0, even though altering the original license is not legally permitted. This creates confusion in the ecosystem and can have legal consequences for those altering the license and those using the model.

Many open (foundation) models are released with technical reports and model cards that provide limited information on the source and treatment of their training data, fine-tuning, or alignment methods [24, 50], and evaluation results often cannot be reproduced independently due to the lack of their disclosure [51]. Furthermore, few disclosures are made about guardrails and if prompts and outputs are altered, filtered, or replaced [52, 53]. Overall, the lack of openness leaves downstream model consumers to rely on limited claims reported by the model producers.

The misrepresentation of models as “open source” is in part due to confusion about the appropriate use of open-source licenses. Many developers do not realize that open-source licenses were designed to cover conventional software code and are not appropriate for the intricacies of ML models [54, 55]. As we discuss in Section 6, open-source licenses cover the model architecture, which is defined in software code, but not the corresponding model parameters. By contrast, model parameters are data and are more aptly governed by open-data licenses than by open-source licenses [56]. Meanwhile the misrepresentation of models as “open source” by companies has also been characterized as “openwashing” [15, 16, 17, 18], where “open” has been used imprecisely to describe “systems that offer minimal transparency or reusability... alongside those that offer maximal transparency, reusability, and extensibility” [14].

Another challenge is that most models have fallen short in their completeness (i.e. the full availability of components from the model development lifecycle, see list in Section 4), only releasing model architectures and final trained parameters. To achieve full transparency, reproducibility, and extensibility, we argue that model producers must go beyond just releasing their model and the trained weights and biases, which is currently the norm. Instead, they should include all artifacts of their work, including datasets for training, validation, testing, and benchmarking, as well as detailed documentation, such as research papers, model cards, data cards, and any usage documentation. Completeness also requires all code used to parse and process data, the code used for training and inference, and any code used in benchmark tests, along with any libraries or other code artifacts that were a part of the model development lifecycle.

### 2.3 MOF: A Novel Approach to Evaluating Model Openness & Completeness

There is not yet an agreed-upon definition of “open source AI” [55]. Broadly, open AI refers to the concept of transparency and accessibility in AI R&D. It entails the sharing of key artifacts associated with the development of models, including data, code, models, and publications, under both open and restrictive licenses, which allow access, inspection, modification, or distribution of models. As mentioned above, open AI also entails grassroots initiatives that have used open collaboration approaches to develop open models [28, 29]. The sharing of models grants the community the freedoms to transparently review capabilities and limitations, identify issues, reuse or extend functionality, and participate in collective advancement. This is enabled through open licenses applied judiciously to key model components, including datasets, model architectures, and trained parameters, which facilitates attribution, safeguards model consumers, and maintains community norms while removing barriers to adoption [57, 58].

The combination of open source, open data, open access, and open science is a powerful and effective way of solving the most pressing issues in AI R&D, including access, explainability, transparency, reproducibility, and safety. The goals of open AI are to accelerate progress through open collaboration, establish trust by allowing system inspection, enable diverse perspectives, and align AI advancement with social benefits [25]. Due to the nascent nature of the open AI movement, new standards are being developed to address shortcomings, including the draft Open Source AI Definition [55]; tools for auditing model explainability, fairness, and robustness [59, 60, 61, 62, 63, 64]; frameworks to evaluate model openness, such as the AAAI Reproducibility Checklist [65] and the NeurIPS 2019 ML Reproducibility Checklist [20]; the establishment of ethics review boards in AI research labs [66]; as well as work by government agencies, including NIST and NTIA in the USA [67] and the AI Safety Institute in the UK [68].

However, prior approaches do not evaluate both the completeness and openness of models. The MOF reinforces existing approaches by objectively evaluating and classifying models based on which components of the development lifecycle are released under open-source licenses. It codifies openness across model development pipelines with informative guidelines, a classification system, and a method for assigning badges to qualified models. Models with licenses that do not impose downstream restrictions are considered open, while restrictive ones are source-available. This differs from the gradient approach to model openness [37], which classifies BLOOM by BigScience [31] and GPT-J by EleutherAI [69] as open. We would classify GPT-J as open because it was released under the OSI-approved Apache 2.0 license, while BLOOM is source-available due to its restrictive, non-OSI-approved OpenRAIL license [70]. Overall, the MOF encourages model producers to strive for complete transparency and usability without restrictions.

### 3 Understanding the Concepts of Openness and Completeness

Before presenting the details of the MOF, we review the concepts of openness and completeness in science and technology. These core tenets form the basis of open science, open source, open data, and open access, which enable transparency, reproducibility, and collaboration in research, and are part of the wider open knowledge movement that believes all knowledge should be shared freely [71]. This section provides an overview of each domain and how they connect to the framework’s goals. Understanding the motivations behind openness clarifies why it is vital to extend these concepts to AI R&D: it facilitates the democratization of AI, which is essential for advancing AI research and innovation, as well as responsibility in AI R&D, including transparency, accessibility, and inclusivity [72].

#### 3.1 Openness

Openness is the practice of freely sharing the methodology, progress, and products of R&D with the public without restrictions on access, inspection, modification, or distribution [73]. Instead of limiting transparency through proprietary terms, openness concerns the release of materials under permissive open licenses tailored to the type of content. This upholds scientific ideals around reproducibility, accountability, and cumulative innovation, while empowering research and developer communities to meaningfully review, discuss, reuse, and extend upon prior work [74]. As we elaborate in Section 3.10, the careful selection of appropriate open licenses facilitates attribution, protects downstream consumers, maintains community ethical norms, and facilitates adoption and impact [75, 58].

We also seek to differentiate between the terms “open” and “complete” in order to make it clear to model consumers exactly what model producers are providing and under what conditions when they say their model is open. Openness is not just about what is included, but importantly under what license each component is released. We believe opening the “black box” of AI will be crucial for continued advances and responsible use [76]. Although open-source licensing is imperative for the code components that are provided for the MOF, our approach to the MOF aligns with wider open science principles and the vision of open AI that requires more than open-source licenses for code components for models to be considered open. For example, non-code elements like datasets and research papers need an appropriate license that suits its format, such as open-data or open-content licenses, which are not currently OSI-approved licenses.

#### 3.2 Completeness

Completeness is a core tenet of open science [74]. We define completeness as the availability of key artifacts produced during the full lifecycle of conducting research or the engineering of a technical product, enabling comprehensive transparency, inspection, evaluation, and reproducibility. In the context of ML, completeness entails releasing all the key components associated with developing an ML model rather than just selected artifacts. It entails sharing the full pipeline that produced a model in a usable form. Comprehensive releases empower unfettered scrutiny into model genetics: curation and treatment of training data, feature engineering, neural architectures, weight evolution, training configurations, model performance across diverse benchmarks, replication of model producer claims, and other byproducts of the model development lifecycle. The MOF encourages model producers to exhibit full completeness, providing all artifacts involved in the model development lifecycle when distributing models. It defines an ascending hierarchy of criteria for releasing key artifacts with the highest bar aligned with open science paradigms. Completeness combined with openness (open licensing) accelerates collective advancement of trustworthy and innovative AI.

We use the term “completeness” borrowed from open science to disambiguate from the multiple uses of the word “openness”, which has unfortunately become a vague and confusing term [14, 17]. Openness is often used to describe not only the licensing used for artifacts but also the availability of artifacts and even the thoroughness of those artifacts. The multiple uses of the term “open” continues to be used in a way that is misleading or does not reveal the specifics of its usage [67]. Packing the term “openness” with multiple definitions, uses, or dimensions does not clearly articulate what aspect of the model is open. For instance, a model producer may claim that their model is “open” but model consumers may not know if it is open because it employs open licenses, because it is made publicly available, because it provides additional components like datasets, or because the components released are thorough or usable. For this reason, we use the term “completeness” to measure the availability of components that are released with models (with the goal of full completeness) and the term “openness” to describe the usage of permissive licenses for components.

#### 3.3 Open Knowledge

Open knowledge is an overarching philosophy and larger movement that encompasses all the preceding areas of openness, revolving around the free and public sharing of information and insights across various domains [77, 78]. This entails making knowledge resources accessible to everyone and contributing to a wider pool of shared understanding. Open knowledge practices also involve ensuring that the information is ethically curated and disseminated, upholding

principles of integrity and respect for intellectual property. The Wikimedia Foundation, Open Knowledge Foundation, and Science Commons are leading organizations in the open knowledge community.

### 3.4 Open Science

Open science refers to the practice of making all stages of the scientific process transparent and accessible to others [74, 79]. This includes publishing research papers, data, source code, code notebooks, and any information or tools needed to replicate research. The goals of open science are to enable reproducibility, collaboration, and facilitate building on previous knowledge to advance scientific research [74]. Open science is critical for credible, ethical, and accessible scientific research that can be reviewed, validated, replicated, and built upon. Open science in AI is sometimes referred to as “open science AI” and is the gold standard for ensuring reproducibility and transparency.

Advances in AI R&D are in part attributed to the sharing of preprints on platforms like arXiv, but much of the training data, model details, and code of SOTA AI systems remain proprietary. The opaque nature of many AI systems limits reproducibility, hinders research, and increases concerns around bias and safety. Transitioning to open datasets, architectures, weights, and code promises to facilitate AI research, innovation, and adoption across the private and public sectors. Overall, openness has repeatedly shown immense power to advance progress, equity, and opportunity across endeavors. The MOF aims to promote the spirit and methodology of open science in the AI R&D community.

### 3.5 Open Access

Open access is the process of making research outputs like publications freely available to read without subscriptions or paywalls, enabling broad dissemination of knowledge. [80, 81]. There are various open-access platforms like Cornell University’s arXiv, which make publications, often distributed under an open license, freely available for review. Furthermore, the adoption of open access policies, mandates, and licenses by journals and conferences have contributed to greater access to research. Before open access, research publications were mostly locked behind expensive journal subscriptions and paywalls, which limited the discoverability and use of knowledge. The open access movement has made more research freely available to all. Open access speeds the dissemination of discoveries to scientists and the public, and it facilitates reproducibility and meta research. As a result, entry barriers to accessing research have greatly reduced and public access to AI research papers has helped advance the field, including many of the developments and enhancements to the transformer architecture that powers the latest highly-capable LLMs.

### 3.6 Open Collaboration and Open Community

Open collaboration encourages cooperative efforts across institutions, disciplines, and borders, involving more inclusive and diverse participation in the development of science and technology [82, 79, 83]. Open community goes beyond open collaboration, and it concerns the creation and sustainability of a shared community with neutral governance, where projects can be worked on collaboratively in an equitable environment that embraces principles of openness. The LF AI & Data and Generative AI Commons are examples of open communities [84].

### 3.7 Open Source Software

Open source software (OSS) involves publishing software code under licenses that grant users independence and control over the technology by allowing inspection, modification, and redistribution of the code without restrictions [54]. The OSS movement has transformed software development over the past few decades: while early closed and proprietary systems limited access, locked in users, and stagnated innovation [85]; nowadays OSS is estimated to be used in 96% of global code bases [86] and to constitute up to 90% of software stacks [87]. It is increasingly being recognized as digital infrastructure [88, 89]. OSI-approved licenses like Apache 2.0 and MIT have been key to enabling worldwide collaborative development, freedom of choice, and accelerated progress [57].

OSS has emerged as an indispensable component of AI R&D [90, 91] and open science at large [92, 93]. OSS presents a myriad of benefits for individuals [94, 95] and enterprises [96, 97]. It encourages the sharing of code and software development methodologies [98], providing a basis for building upon existing work and contributing to the advancement and democratization of science [99, 100]; it provides learning, skill development, and career development opportunities [28, 101]; it reduces software development and testing costs [102, 103, 104]; and it facilitates the development of open standards [98, 105], among others. The benefits of OSS do not come without risks, especially at the hand of bad actors and in light of vulnerabilities [106, 107]. Yet a wide user base and the sharing of knowledge enables OSS projects to quickly identify vulnerabilities and fix issues. A good example is the identification of the recent XZ attack (CVE-2024-3094) and public reporting by the open source community [108, 109].

### 3.8 Source Available

Source available should not be confused with open source. Source available originated from conventional software development, where a developer provides access to the source code, but the licenses are not open-source. This means they include restrictions that consumers must fully understand before agreeing to use it. Some have referred to these projects as open access, but this is a misnomer since open access applies to documentation without paywalls. Most open-washed projects are examples of source available due to their restrictive licensing [15, 16].

### 3.9 Open Data

Open data refers to the public release of datasets, databases, and other structured data used for research, enabling access and reuse [110, 111]. This practice upholds scientific reproducibility, allows reanalysis, and spurs innovation [112]. Standard policies and formats are often employed to ensure quality and usable data sharing. Open content, on the other hand, refers to the sharing of creative materials and unstructured data. Both open-data and open-content licenses exist, with open-data licenses often applicable to both data and content. Open data emphasizes the standardization of datasets, addressing transparency and requiring comprehensive descriptions of data collection methods and assessments for intrinsic bias. Furthermore, accessibility is a cornerstone of open data, with datasets expected to be readily available without personal requests or paywalls, promoting transparency and enabling scrutiny.

Historically, many research fields had cultures of data secrecy that impaired reproducibility and knowledge building. Openly sharing data enables reanalysis, reproducibility, and new applications [113, 110]. For instance, government open data initiatives provide transparency of government operations and promote innovation in and for the public sector [114, 115]; opening clinical trial data facilitate pharmaceutical research [116] and open genomic databases enable bioinformatics breakthroughs [117]; and open climate data [118, 119] have fuelled research and innovation to combat climate change. While better standards and tooling around open data publishing are still needed, the value of open data is clear. In the context of AI R&D, the Datasets and Benchmarks track at NeurIPS underscores the paramount importance of openly releasing machine learning datasets [23].

### 3.10 Open Licenses

Open licenses are legal mechanisms that allow content and artifacts to be freely accessed, used, modified, and shared under permissive terms. They are essential for operationalizing open science, open data, and open-source ideals [57]. Different licenses have emerged for addressing rights, responsibilities, and permissible usage for data, publications, code, and other research outputs. Open licenses solve key problems with closed, restricted systems, including:

- Enabling free access without paywalls or subscriptions
- Allowing reproduction, analysis, and extension of work
- Disseminating contributions back to the community
- Progressing cumulatively by building on prior ideas
- Fostering collaboration across organizational and geographic boundaries
- Promoting transparency and accountability
- Mitigating anti-competitive behavior or rent-seeking

For research papers and scholarly works, Creative Commons (CC) licenses are widely adopted, which allow free distribution and reuse with conditions, such as requiring attribution and allowing commercial use and derivative works. Common choices for open licenses are CC-BY (attribution) and CC-BY-SA (share alike). Using permissive CC licenses for papers, technical reports, and documentation provides rights to reproduce, expand, and translate the works [58].

For software code, many open-source licenses have been developed. The Open Source Definition and the list of approved open-source licenses is maintained by the OSI [54]. Using OSI-approved open-source licenses encourages community review and contributions to code, promoting quality and shared progress [75]. Prominent examples include the MIT, Apache 2.0, and the 3-Clause BSD license, which allow inspection, modification, and redistribution of code while requiring preservation of copyright and license terms. Alternative licenses, such as the Llama 2 license, OpenRAIL, and AI2 ImpACT licenses, are not considered open-source licenses due to their restrictions on usage [16].

For datasets, typical licenses are Creative Commons licenses, particularly Creative Commons Zero (CC0), CC BY (attribution) and CC BY-SA (Attribution-ShareAlike), as well as Linux Foundation's Community Data License Agreement (CDLA-Permissive) and the Open Data Commons licenses like Public Domain Dedication and License (PDDL) and the Open Data Commons Attribution License License (ODC-By). They provide terms for sharing data openly while addressing concerns, such as attribution, permissive usage, and liability [58].

## 4 MOF Components

The MOF defines criteria for classifying the degree of completeness and openness across all aspects of a model’s development lifecycle. Models are classified in a **three-tier system** (see Table 1) based on the specifics of which components are released openly. The higher the class indicates a more complete distribution that promotes more transparency and enables reproducibility, auditing, and downstream use. The MOF has 17 components to fulfil completeness of model artifacts, which cover the code, data, and documentation that are part of the model development lifecycle. Four components—datasets, supporting libraries and tools, model metadata, and sample model outputs—are optional, with the caveat that datasets must be included for Class I (any or no license). The distribution includes an additional component, the MOF configuration file to comply with the MOF requirements.

### 4.1 Datasets

Data is the lifeblood of ML models and is the most often held back element in the release of a model. Training data is data used for any form of model training including pre-training, fine-tuning, alignment using reinforcement learning techniques, or data used for other methods that otherwise modify the weights of the model. Datasets also include data used for model validation and testing as well as data that may be used with benchmark tests. The datasets component may also include tokenized datasets when present. Data can be any form or combination of media, whether text, code, images, videos, audio, 3D objects, URIs, and any other data used for training, validation, and testing purposes. Datasets also include any metadata, from annotation data, such as labels, bounding boxes, and key points, to attribution, bitrates, resolution, and other metadata that may be relevant to a dataset used in the model development process.

The datasets used to develop the model ideally should be released under an open license allowing unrestricted access, modification, and reuse for any purpose, preferably Creative Commons CC-BY-4.0 or CC-0. We acknowledge that most pre-training data is subject to copyright and therefore it is not possible to license the data. To this end, datasets are an optional component, with the caveat that datasets must be included for Class I (with any or no license). Having access to the training data, whether pre-training, fine-tuning, alignment, or any other data, enables reproducibility and validation of the training process. Any limits on sharing due to privacy or sensitivity should be documented. It is preferable that both pre- and post-processed data are supplied. However, if this is not possible due to the size of a dataset, providing links to any curated raw datasets online is sufficient when accompanied by data preprocessing code.

### 4.2 Data Preprocessing Code

The data preprocessing code concerns the code used for the preprocessing, cleaning, and formatting of the training, validation, and testing data used in the development of a model. It may also include code used to transform fine-tuning data and code used for alignment tasks like Reinforcement Learning from Human Feedback (RLHF) [120]. Other data preprocessing code may include code for data ingestion when appropriate, feature engineering, data augmentation, and tokenization. Sharing code for data preprocessing aids in reproducibility and can help uncover data-related biases. The data preprocessing code must be released using an OSI-approved license that covers OSS.

### 4.3 Model Architecture

The model architecture is the core of any ML project. It can include the ML algorithms, neural network layout, connectivity, activations, and other architectural elements. While the model architecture is often closely tied to the trained model parameters, sharing the architecture alone allows others to understand the structure of the model without necessitating the release of the fully trained model. The model architecture should be fully described in the paper and shared as open-source code. This enables implementation, analysis, extensions, adaptations and unrestricted usage of the model or models. The model architecture is a code artifact and to be considered open, must be released under an OSI-approved open-source license that does not limit its usage and derivative works.

### 4.4 Model Parameters

Trained model parameters must be released under an open license that allows for unrestricted usage, study, modification, and redistribution of model weights. For deep learning models, it is essential to include checkpoints from key intermediate stages of training as well as the final optimizer state, enabling the reconstruction of the full model lifecycle and reproducibility. At a minimum, the final model parameters and optimizer state (when applicable) must be distributed in an acceptable format, either compressed or uncompressed. The format should be compatible with deep learning frameworks, such as TensorFlow, Keras, PyTorch, or the framework-independent ONNX file format.

To date, model producers have been releasing model parameters (i.e., weights and biases) using an open-source license, such as Apache 2.0 and MIT, even though model parameters are not compatible with OSS licenses. Since model parameters are in fact data, producers should use an open data license, such as CDLA-Permissive-2.0. Although licenses designed for OSS are permissive and indemnify the developer from liability, open data licenses are better suited to data-specific considerations such as privacy, ethics, and data rights. Most permissive licenses do not refer to data directly and do not address the ability to modify and redistribute model parameters. This gap could result in a legal obligation to any model consumer if the model producer were to implement royalties after widespread adoption of their model. This is a legal gray area that remains untested. The model architecture and model parameters should be saved independently in different files for distribution, as each one requires a different format-appropriate open license. This separation allows each component to be studied, modified, redistributed, and used independently of the other.

#### 4.5 Model Metadata

Model metadata are an optional component. Model metadata refers to additional information about the model, beyond the model parameters and architecture, such as the version of the framework used to create it and custom tags or descriptions provided by the developer, including model and data lineage information. There is no particular requirement or profile for this type of metadata, and it can include any information the developer would like to provide with the shipped model. This metadata can be helpful for model management, especially when working with multiple versions of models or conducting experiments. Often the metadata is exported from or loaded by a metadata store. Any model metadata should use an open-data license such as CDLA-Permissive-2.0 to ensure it can be freely used and shared.

#### 4.6 Training, Validation, and Testing Code

The full code for training, validating, and testing the model should be open-sourced, including model construction, training loop, hyperparameter selection, and checkpointing. Any fine-tuning code, reinforcement learning code, or methods that modify model parameters or implement adapters affecting model performance must be included. This enables reproducible end-to-end training. Comments explaining the approach should be included, ideally following PEP 8 style guide for Python code. Including log files generated during training provides deeper insights and is recommended. The training, validation, and testing code must be released under an OSI-approved open-source license, while log files should use a permissive open-content license like CC-BY-4.0.

#### 4.7 Inference Code

Code for performing inference with the trained model must be shared under an open-source license. This includes any data preprocessing or postprocessing required during inference. It can include any model optimizations and dependencies like external libraries. It fundamentally includes any code required to fully replicate the benchmark results presented in the research paper for the project. The availability of inference code facilitates complete replication of the performance of the model, and it informs the model consumer about how to use the model most effectively for their applications. The inference code must be released under an OSI-approved open-source license.

#### 4.8 Evaluation Results

Evaluation results, including quantitative metrics and results from model evaluation, must be reported in the research paper or technical report. Tests can evaluate factors such as model efficiency, accuracy, performance, fairness, bias, toxicity, and truthfulness. Producers must include benchmark test results, whether industry standard or custom-developed. For industry standard benchmarks, the test suite name, test name, and version number must be included with the results. Custom benchmarks, whether in code or any form of media, must be included in full for validation. The evaluation results should be summarized in the technical report and research paper, depending on the MOF class. Raw outputs of the model evaluation should be distributed for easy verification, using an open license like CC-BY-4.0.

#### 4.9 Evaluation Code

Evaluation code, evaluation data, and evaluation results are separate components in the MOF. This is due to the fact that some benchmarks are written in code and other benchmarks only use data, for instance text used to evaluate an LLM or images used to evaluate a computer vision model. Many benchmark tests are a combination of both code and data used to evaluate a model, which includes the scripts needed to load the data and run benchmark tests. Since code and data require different licenses, they are separate components. Depending on the nature of the model and the methods used to evaluate it, the distribution may include one or both of evaluation code and data. Any code used for model evaluation and benchmarking must be included and distributed under an OSI-approved open-source license.



#### 4.10 Evaluation Data

When a model is evaluated using data, such as text, images, videos, audio, or 3D data, the evaluation data must be included in the distribution. However, if the model is not evaluated with data, then including the evaluation data is not necessary. In cases where the model producer relies on widely disseminated standard benchmark tests, it is sufficient to describe them in the technical report and whitepaper, along with the version of the test, rather than including them in the distribution. If the evaluation data is included in the distribution, it must use a permissive license appropriate for data or content, such as CDLA-Permissive-2.0, CC-BY-4.0, or CC0.

#### 4.11 Supporting Libraries and Tools

Supporting libraries and tools are an optional component. Releasing any supporting code libraries, utilities, or tools developed in the course of the research under an open-source license makes them available for wider use. This could include data loaders, visualization code, simulation environments, etc. The use of existing and custom open-source tools should also be documented. Other tools and libraries may include:

- Software libraries and frameworks used in model development along with version details.
- Tokenizers: Code used to tokenize text and any data used to train the tokenizer (if used.)
- Hyperparameter search code: Code for automating hyperparameter tuning (if used).
- Compute infrastructure code: If specialized compute infrastructure was built to scale training, the setup code could be released.
- Monitoring code: Code for tracking experiments, metrics, artifacts etc. during model development is often useful to open source as well.
- Containerization files: Dockerfiles or other container packaging to distribute the model could be shared.
- Frontend/visualization: Any web/mobile frontends or visualizations built on top of the model outputs could be released as open source.
- Deployment orchestration: Infrastructure-as-Code templates for deploying the model to production.
- Model integration code: Wrapper code/SDKs to integrate the model into downstream applications.
- Interactive demos: Links to hosted interactive demos of the model through Jupyter, Streamlit, etc.

Most libraries and tools will already have a license, so only if the model producer creates their own libraries or tools would they need to include them with the distribution and use an OSI-approved license for the software.

#### 4.12 Model Card

A model card provides metrics, usage guidance, and details about a model [22]. Model cards should cover model details, intended uses, factors, evaluation, risks, and mitigations related to the model. This provides transparency into model behavior. The model card itself must use a permissive license that covers documentation, ideally CC-BY-4.0.

#### 4.13 Data Card

A data card provides summary statistics and key information about a dataset to enhance understanding of its composition [23]. Following guidelines from the Data Nutrition Project [121], data cards should describe various aspects of the dataset, including the features, instances, intended uses, motivation, and collection process. Data cards help identify potential biases in datasets and guide proper usage by downstream usage. They also contribute to reproducibility and transparency by detailing the entire data preparation process. The data card must be released under a permissive license that covers documentation, with CC-BY-4.0 being an ideal choice.

#### 4.14 Research Paper

The research paper details the model methodology, results, and analysis, following open science principles for accessibility and transparency. We suggest structuring the paper with an abstract, introduction, related work, methods, results, discussion, conclusion, and references. The paper must be released under an open license, ideally CC-BY-4.0, shared on an open-access platform like arXiv, and included in the model distribution.

#### 4.15 Technical Report

The technical report is less detailed than a research paper. It provides necessary documentation for the model consumer to understand performance, usage, and implications, but not enough to reproduce the model. The technical report is optional if a research paper is included. The goal is to characterize model capabilities and provide adoption and impact guidance. The technical report must be released under an open license for documentation, ideally CC-BY-4.0 or CC0, on an open access platform, and must be included in the distribution for permanence.

#### 4.16 Sample Model Outputs

Sample model outputs are an optional component. If they are included in the distribution, they must be shared publicly without copyright or restrictions where legally permitted to allow for redistribution with the release. These outputs can take various forms, such as text samples, images, videos, software code, audio, 3D assets, metadata, or any other potential output generated from the model, including predictions and probabilities. In certain sensitive domains, generated examples can be anonymized or simulated if needed. Sample model outputs help others perform a quick evaluation of the model's performance and provide a glimpse into its capabilities. If the model outputs are not copyrightable, they should be released without a license, and this should be noted in the LICENSE file. It is important to note that while sample model outputs are recommended, they are not a requirement for the MOF. Additionally, the MOF does not consider the actual model outputs generated by the model consumer during inference.

#### 4.17 Model Openness Configuration File

The MOF configuration file is a crucial component of any model distribution, serving two primary purposes. It informs model consumers about the components included in the release; and it specifies the licenses under which each component is distributed. The MOF configuration file enables platforms that host models to understand the contents and licensing of the model distribution. The file itself is distributed under the Creative Commons CC-BY-4.0 license.

## 5 Model Openness Framework Classes

### 5.1 MOF Structure

The MOF categorizes ML components into three distinct classes: Class I, Class II, and Class III. Each class builds upon the previous one, with Class III being the least complete and Class I being the most complete (see Table 1). This approach is more meaningful than a calculated index, as it guides model producers in providing essential components released under open licenses for each tier of the framework. As the class of the MOF increases, the producer moves closer to a more complete distribution that best aligns with the principles of open science in AI. To qualify for a particular class, the producer must provide every required component for that class. Each component must be released using an appropriate open license from Table 2 to qualify the entire project at the specified class level.

### 5.2 MOF Class Descriptions

The 3 classes of the MOF represent ascending levels of model completeness and openness. We describe the distinguishing aspects of each tier beginning with the lowest class.

#### 5.2.1 Class III. Open Model

In the MOF, Class III is the entry point and contains the minimum required components that must be released using open licenses. If not all of these components are included in a release and all components do not use an open license then the entire release cannot be considered open under the MOF. The Open Model class covers the following:

- Core model architecture and the final set of parameters
- Light documentation conveying capabilities and characterization of the model and data.

Class III contains all the components required to study, modify, redistribute, and build upon a model without restrictions, including for commercial and educational purposes. The inclusion of the model architecture, final weights and biases, and documentation (including the technical report, evaluation results, model and data cards) provides the necessary information to work with the model and understand its capabilities, constraints, and the nature of the training data. However, this class lacks completeness and robustness for full reproducibility and the transparency needed to confirm all claims made by the producer. It also lacks sufficient components to evaluate the model, including the training data.

MOF Class	Components Included
<b>Class I. Open Science</b>	<ul style="list-style-type: none"> <li>• Research Paper</li> <li>• Datasets (any license or unlicensed)</li> <li>• Data Preprocessing Code</li> <li>• Model Parameters (intermediate checkpoints)</li> <li>• Model Metadata (optional)</li> <li>• And all Class II Components</li> </ul>
<b>Class II. Open Tooling</b>	<ul style="list-style-type: none"> <li>• Training Code</li> <li>• Inference Code</li> <li>• Evaluation Code</li> <li>• Evaluation Data</li> <li>• Supporting Libraries &amp; Tools (optional)</li> <li>• And all Class III Components</li> </ul>
<b>Class III. Open Model</b>	<ul style="list-style-type: none"> <li>• Model Architecture</li> <li>• Model Parameters (final checkpoint)</li> <li>• Technical Report</li> <li>• Evaluation Results</li> <li>• Model Card</li> <li>• Data Card</li> <li>• Sample Model Outputs (optional)</li> </ul>

Table 1: Model Openness Framework Classes and Components

### 5.2.2 Class II. Open Tooling

Building upon Class III, level II provides model consumers the complete codebase including libraries and tools needed for training, assessing and testing models themselves. Added elements include:

- Full training and inference code
- Benchmark tests to validate and quantify performance
- Libraries and tools to ease integration and to complete the codebase (optional)

This tier is an intermediate step between an open model and open science, providing a model consumer with information to test a model producer’s assertions. It also allows a model consumer to perform debugging, and it allows for enhancements to model functionality. Although it does provide insights into the training process, it does not include the actual datasets. It is also lighter on documentation, which limits a deeper understanding of the model’s intricacies.

### 5.2.3 Class I. Open Science

The top tier aligns with ideals of open science: the sharing of all artifacts needed for end-to-end transparency, reproducibility, and collaboration. This includes:

- A detailed research paper conveying the genesis of the model and its evolution
- Raw training datasets used in the training of the model (any license or unlicensed)
- Checkpoint weights showcasing full model evolution
- Log files providing yet more low-level insights

Fulfilling Class I empowers the community to inspect models through the model lifecycle along multiple fronts, representing the gold standard for completeness and openness rooted in scientific principles.

### 5.3 Hybrid Releases

Openness has always been a binary decision in the open-source movement; software is either open-source or not, with no in-between [54]. A developer either released their software under an OSI-approved license or they did not. If any essential component was not released under an open-source license, the entire release was no longer considered open source. The MOF follows this principle. When any component is not released using an open license as described in Table 1, that component is not deemed open and does not qualify for an MOF class. Removing a component that moves the project into a lesser class is acceptable if all remaining components are released with open licenses.

To qualify as a Class III project, the model, its parameters, and a technical report that describes the work along with evaluation results and model and data cards must be released with open licenses. If not, the project cannot be considered open. This includes projects that use modified open licenses and implement restrictions or acceptable uses.

It should be noted that the MOF classifies models and their components on completeness when they are open. The reader should not confuse the classification system as being a gradient measure of openness [37], but rather a measurement of the completeness of a release in adherence with open science principles [25, 79, 92].

## 6 Model Openness Framework Acceptable Licenses

Table 2 provides an overview of acceptable licenses for each component. The table categorizes each component into one of three domains: Data, Model, or both. Additionally, the content type of each component is classified as data, code, or documentation. The table specifies standard open licenses that should be used for releasing each component, while allowing some flexibility for equivalent licenses. By providing a comprehensive scope, the MOF encourages opening the entire pipeline that produces, evaluates, and applies a model. This approach offers multiple perspectives into the model's inner workings, promoting transparency and reproducibility in open model development.

Component	Domain	Content Type	Accepted Open License
Datasets	Data	Data	Preferred: CDLA-Permissive-2.0, CC-BY-4.0 Acceptable: Any including unlicensed
Data Preprocessing Code	Data	Code	Acceptable: OSI-approved
Model Architecture	Model	Code	Acceptable: OSI-approved
Model Parameters	Model	Data	Preferred: CDLA-Permissive-2.0 Acceptable: OSI-Approved, Permissive Open Data Licenses
Model Metadata	Model	Data	Preferred: CDLA-Permissive-2.0 Acceptable: CC-BY-4.0, Permissive Open Data Licenses
Training Code	Model	Code	Acceptable: OSI-approved
Inference Code	Model	Code	Acceptable: OSI-approved
Evaluation Code	Model	Code	Acceptable: OSI-approved
Evaluation Data	Model	Data	Preferred: CDLA-Permissive-2.0 Acceptable: CC-BY-4.0, Permissive Open Data Licenses
Evaluation Results	Model	Documentation	Preferred: CC-BY-4.0 Acceptable: Permissive Open Content Licenses
Supporting Libraries & Tools	Model	Code	Acceptable: OSI-approved
Model Card	Model	Documentation	Preferred: CC-BY-4.0 Acceptable: Permissive Open Content Licenses
Data Card	Data	Documentation	Preferred: CC-BY-4.0 Acceptable: Permissive Open Content Licenses
Technical Report	Model & Data	Documentation	Preferred: CC-BY-4.0 Acceptable: Permissive Open Content Licenses
Research Paper	Model & Data	Documentation	Preferred: CC-BY-4.0 Acceptable: Permissive Open Content Licenses
Sample Model Outputs	Model	Data or Code	Unlicensed

Table 2: Model Openness Framework Components and Licenses

## 7 Implementing the Framework

### 7.1 MOF Process Overview

Unlike other frameworks that attempt to dictate how model producers should build and train their models or create a release path on how models should be released, we take a more objective approach by evaluating models based on their completeness and openness. This approach does not constrain model producers into a single methodology but rather lays out a pliable process that acts as a guideline to help model producers create the most complete and open models. At the completion of the process the MOF provides model producers with a badge for their MOF class that clearly demonstrates to the public their commitment to both completeness and openness.

The MOF process generally follows these steps:

1. Inventory of artifacts
  - (a) Comprehensively list all artifacts involved in creating the model (data, code, documentation, etc).
  - (b) Capture details like component names, component locations, versions and licenses.
2. Map to MOF components
  - (a) Align inventory items to the 16 components defined in Section 5.
  - (b) Multiple inventory elements may map to a single standard component.
3. Verify licenses
  - (a) For each MOF component present, check if it uses an acceptable open license from Table 2.
  - (b) If licenses are incompatible, the model cannot be classified.
4. Determine completeness
  - (a) Check inventory against the component list for the 3 classes in Table 1.
  - (b) Classify model at the highest tier where all required components in the class employ open licenses.
  - (c) Model meets Class III at a minimum when using open licenses.
5. Generate MOF.JSON
  - (a) Create the MOF.JSON file, either using the Model Openness Tool (MOT) or manual means.
  - (b) Include all artifacts, licenses, locations and other required data to meet the MOF requirements.
6. Self-assert classification
  - (a) With inventory, mapping, and MOF.JSON file finalized, the model producer asserts the appropriate class using the Model Openness Tool (MOT) or through self-assessment.
  - (b) The model producer must stand behind their completeness and openness claims.
7. Badging and validation
  - (a) The model producer uses the MOT for badging classified models.
  - (b) MOT provides the MOF.JSON file and badge code for inclusion with project files.
  - (c) Community helps ensure accurate labeling by filing disputes.

This process determines a model's location on the spectrum, guiding model producers in improving openness and consumers in evaluating fitness of models for their usage.

### 7.2 Preparing the Distribution

All projects must include a LICENSE file that describes the licenses used for the project. Conventionally a LICENSE file would include a single license, however it is recommended that the LICENSE file include all licenses that apply to the project. For instance if software is covered under Apache 2.0 and all documentation and data use CC-BY-4.0, then the text of both licenses should be included in the LICENSE file in their entirety including the license heading in order to distinguish what text belongs to which license. Alternatively, a distribution can contain different LICENSE files that are bound to the different components included in the distribution. Ideally the LICENSE files for each component should be located in the base directory of the component that they cover. The MOF.JSON file records the path to the appropriate LICENSE file for each component included in the distribution and facilitates both the per component LICENSE method and the single LICENSE file method.

In addition to the LICENSE file, the distribution must include an MOF.JSON file providing details about the MOF version, release details, included components, and their licenses. This file can be generated with the MOT maintained

by the Generative AI Commons at [122] or created manually or automatically. It is important to note that when a component is not released with the distribution, it should not appear in the MOF.JSON file. When a component is released but does not use an open license or it uses a custom license, it should not be included in the MOF.JSON file either. The MOF.JSON file only references components that are released using an open license.

### 7.3 MOF.JSON Structure

The MOF JSON file is structured as a single MOF object defined at the root of the JSON file (see GitHub [123]). Specifically, under the root there are three required, nested objects with their own set of variables:

- **Framework:** This object contains the details related to the framework itself, including the following required variables:
  - **name:** The name of the framework. The variable type is string.
  - **version:** The version number of the framework. The variable type is string.
  - **date:** The publication date of the framework. The variable type is string in YYYY-MM-DD format.
- **Release:** This object contains the details of the model being released. There are a number of variables:
  - **name:** The name of the release. The variable type is string.
  - **version:** The version of the release, which can be the parameter count or another identifier that distinguishes the model from previous versions and versions of the same model with different parameter counts. The variable type is string.
  - **date:** The date of the release. The variable type is string in format “YYYY-MM-DD“.
  - **type:** The nature of the model, i.e., language model, image generation, audio generation, image classification, statistical ML, or any number of other types of models. The variable type is string.
  - **architecture:** The model architecture employed, i.e., transformer, diffusion, GAN, NERF, VGG, Resnet, K-means, or any other type of model architecture. The variable type is string.
  - **treatment:** Any type of post-training treatment, like fine-tuning, constitutional alignment, RLHF or any other treatment that otherwise modifies the parameters of the original model. If no treatment has been applied then this variable is an empty string. The variable type is string.
  - **origin:** The original model, generally this is the foundation model. If this is not a foundation model in the release, then this variable contains the name and version of the model that was modified. The variable type is string or left empty for foundation or non-derivative models.
  - **producer:** The name model producer or publisher, could be a company, organization, group or individual. The variable type is string.
  - **contact:** The email address for the model producer or publisher. The variable type is string.
  - **mof\_class:** The qualifying MOF class of the release as generated by the Model Openness Checker. The variable type is integer.
- **Components:** This object contains a list of components that are included with the model distribution, as well as each component’s details:
  - **description:** A text description of the component. Using the default values is acceptable. When introducing a new component beyond the standard components, include a description of the component.
  - **location:** The location of the component within the distribution, full path is required in UNIX format with leading slash for the root directory. The variable type is string.
  - **license:** The SPDX identifier of the license(s) used for the component. If multiple licenses are used for a single component, often the case for libraries and tools, they must be provided in a comma-separated list. The value must use a valid SPDX license identifier [124]. The variable type is string.
  - **license\_path:** The location of the LICENSE file for the component within the distribution, full path is required in POSIX format with leading slash for the root directory. More than one component can point to the same LICENSE file. In the event the component employs multiple licenses, the LICENSE file should contain the text for all the licenses used. Alternatively, multiple license files may be specified, each separated by a comma. However they must correspond in order to the comma separated list of license names provided in the license variable. The variable type is string.

### 7.4 Class Assignment

The MOF relies on self-reporting and projects are not classified by a central authority. LF AI & Data Generative AI Commons will provide a web interface, the MOT, that allows model producers to fill out a web form with the details of their project and in turn the MOT informs the user how their project lines up with the classes in the MOF.

## 7.5 Badging System

The MOF is designed to be both informational and actionable. As such the Generative AI Commons is implementing a badging program, similar to the OpenSSF Best Practices Badge Program [125]. The badging system is a part of the MOT [122], and is a free service that allows model producers to perform the following:

- Perform a check the completeness and openness of their model distribution and display which MOF class their model meets
- Receive recommendations on which licenses to use for which components
- Generate an MOF.JSON file for their distribution
- Be provided with code to insert into their README.md file in their Github repository
- Track their model's ranking amongst other models on the MOF scoreboard

For model consumers, they can do the following:

- View the MOF scoreboard to see which models are the most complete and open
- Drill down into model distributions to see which ones meet their completeness and openness requirements
- Quickly see which MOF class a model has attained in the project's Github repo
- Validate that a model has attained an MOF class
- Submit a dispute if they believe that a model is being misrepresented as complete or open

It is incumbent upon the producer of an ML model and its components to accurately include the results of either the MOT or accurately identify the components and licenses included in the distribution in the MOF.JSON file and specify the class the project qualifies for. Misrepresentations will only harm the reputation of the model producer.

## 7.6 Disputes

The MOF relies on the honesty and transparency of researchers and developers to accurately classify models and to state which components with which licenses they include. Therefore, we also rely on the community to identify projects that have been misrepresented as open and notify the organization that hosts the project about their concerns.

## 8 Benefits of the MOF

The adoption of the MOF by the AI community brings many advantages, including but not limited to:

- **Clarity:** Clearly defines what components are included and under which license each is distributed, in order to understand the acceptable forms of use and whether a project is complete and truly open or not.
- **Openness:** By classifying models and their artifacts at increasing degrees of openness, the MOF will help push model producers towards creating the most complete and open models, helping to advance open science and both academic and commercial usage.
- **Reproducibility:** Comprehensive availability of data, code, and models enables others to independently reproduce results and identify sources of errors, bias or disparities. This strengthens scientific rigor.
- **Transparency & Explainability:** Opening model architectures, weights, training code, and documentation sheds light on how models work and behave. This builds appropriate trust and aids inspecting for issues.
- **Data Provenance:** Origination and attribution can be determined when the data and its details are released. This can be helpful in tracing bias in models or identifying sources of PII leakage.
- **Accountability & Fairness:** Public data and models can be audited for unwanted biases and harms. Model producers can be notified of problems discovered by the community.
- **Continuous Improvement:** Model producers and consumers can build on open models instead of starting from scratch, accelerating innovation and progress in AI.
- **Collaboration:** Sharing open resources allows model producers and consumers across different fields and organizations to pool knowledge and capabilities.
- **Education & Learning:** Data, code, and models support teaching and learning about AI. Students and new researchers and developers can more easily enter the field.
- **Regulation:** Openness makes models more amenable to oversight and governance, unlocking policy options.

## 9 Limitations and Criticisms

### 9.1 Known Limitations

We acknowledge several limitations and likely criticisms:

- The MOF is designed for deep learning artifacts but does not transfer directly to every form of learning in AI. It is applicable to classical ML but does not translate entirely to all aspects of reinforcement learning.
- Model producers are expected to be honest about the availability of the components released with their models and the openness of licenses for each component as well as the completeness of both in their release.
- It requires convincing model producers who may be reluctant to share their work publicly without restrictions.
- Openness goals must be balanced with privacy, IP, institutional policies, and commercialization pressures.
- Classifying models ignores their actual functionality, and bias, safety, and other harms remain a concern. However, openness with models and data enables external audits of quality and completeness.
- Simplicity of classification may not capture all nuances. But enhancement of the rubric may occur.
- It does not address the use of copyrighted materials in training data, an area currently being addressed through courts and legislation. The MOF requires data to be open using an open license; however, we encourage model producers to use authorized data in training models and respect copyrights [126].

### 9.2 Out of Scope

The MOF is not designed to solve all issues related to AI and openness, and its effective implementation will rely on the AI community to be transparent and honest in their reporting of the components of the models that they release and the licenses applied to each. The MOF does not intend to address any of the following as they are best addressed through alternative methods and means: AI safety (including bias, fairness, and trustworthiness), performance testing, red-teaming, security and privacy, components related to model serving, and model provenance.

## 10 Conclusion

The MOF provides a clear, actionable methodology for assessing and enhancing the openness and completeness of ML models. It comprehensively outlines specific components that should be openly released, including training data, code, model architecture, model parameters, and documentation, among others, as well as with which licenses. This framework gives model producers a roadmap to follow for reproducible and ethical AI development. By adopting open licenses, as prescribed by the MOF, collaboration and community engagement are enabled, allowing the freedom to use, modify, and distribute models and components under the terms of its license. The tiered classification system incentivizes releasing models with increasing levels of completeness. The widespread adoption of the MOF promises to establish completeness and openness as primary criteria alongside the core tenets of responsible AI, ultimately promoting a more transparent and responsible advancement of AI R&D. We encourage model producers to incorporate the framework into their policies to make open science the standard for model distribution, as well as the wider AI community to recognize and reward complete and open distribution of models. Realizing this vision requires a concerted effort by all AI stakeholders, including researchers, developers, institutions, companies, and governments, to embrace both completeness and openness as core tenets. The immense benefits for science, business, and society make pursuing model transparency well worth the challenge. With carefully designed incentives, policies, and community norms, open source and open science ideals can become the norm in AI, rather than the exception. By working together across domains, we can shape AI advancement to be as complete, open, ethical, and empowering as possible. The MOF provides practical guidance for this journey towards trustworthy and democratized AI.

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## **A About the Generative AI Commons**

The Generative AI Commons is a community-driven initiative at the Linux Foundation's AI & Data Foundation. It is a vendor neutral forum and open participation initiative focused on advancing principles of open science and open source in generative AI. The Generative AI Commons is dedicated to fostering the democratization, advancement and adoption of efficient, secure, reliable, and ethical Generative AI open source innovations through neutral governance, open and transparent collaboration and education. More about the Generative AI Commons, as well as details and links to join the community can be found at <https://genaiccommons.org>.

## **B About the LF AI & Data Foundation**

The LF AI & Data Foundation is a global not-for-profit foundation that hosts critical components of the global AI & data technology infrastructure at the Linux Foundation. It brings together the world's top developers, end users, and vendors to identify and contribute to the projects and initiatives that address industry challenges for the benefit of all participants. More about the LF AI & Data Foundation can be found at <https://lfaidata.foundation/>