

Towards Open Federated Learning Platforms: Survey and Vision from Technical and Legal Perspectives (TBD)

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Traditional Federated Learning (FL) follows a server-dominated cooperation paradigm which narrows the application scenarios of FL and decreases the enthusiasm of data holders to participate. To fully unleash the potential of FL, we advocate rethinking the design of current FL frameworks and extending it to a more generalized concept: Open Federated Learning Platforms. We propose two reciprocal cooperation frameworks for FL to achieve this: query-based FL and contract-based FL. In this survey, we conduct a comprehensive review of the feasibility of constructing an open FL platform from both technical and legal perspectives. We begin by reviewing the definition of FL and summarizing its inherent limitations, including server-client coupling, low model reusability, and non-public. In the query-based FL platform, which is an open model sharing and reusing platform empowered by the community for model mining, we explore a wide range of valuable topics, including the availability of up-to-date model repositories for model querying, legal compliance analysis between different model licenses, and copyright issues and intellectual property protection in model reusing. In particular, we introduce a novel taxonomy to streamline the analysis of model license compatibility in FL studies that involve batch model reusing methods, including combination, amalgamation, distillation, and generation. This taxonomy provides a systematic framework for identifying the corresponding clauses of licenses and facilitates the identification of potential legal implications and restrictions when reusing models. Through this survey, we uncover the current dilemmas faced by FL and advocate for the development of sustainable open FL platforms. We aim to provide guidance for establishing such platforms in the future, while identifying potential problems and challenges that need to be addressed.

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1 INTRODUCTION

In recent years, the barriers to the development of Artificial Intelligence (AI) have been broken down with the rapid progress of ABC technologies in computing: AI, Big Data, and Cloud Computing, as well as the emergence of cost-effective specialized hardware [207] and software [96]. This has led to the world entering the third wave of AI development: Deep Learning [113]. The success of current data-driven AI relies on massive amounts of training data and follows a gather-and-analyze paradigm [227], which confronts with challenges of complying with rigorous data protection regulations such as OECD Privacy Guidelines [211] and General and Data Protection Regulation (GDPR) [217]. So although data-centric AI is now the mainstream, a novel model-centric distributed collaborative training framework called Federated Learning is gaining popularity in both academia and industry due to its advantages in complying with privacy regulations. So although data-centric AI is currently mainstream paradigm, Federated Learning [128], a novel model-centric distributed collaborative training framework, is gaining popularity in both academia and industry for its advantages in complying with privacy regulations [213].

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According to the definitions of IEEE Standard for Federated Machine Learning (FML, aka FL) [200], *FL is a framework or system that enables multiple participants to collaboratively build and use machine learning models without disclosing the raw and private data owned by the participants while achieving good performance*. For example, a typical workflow of FL systems is that the entity with modeling demand (aka FL server) first deploys the FL services and initializes the model training task, and then distributing this task to participants with training data (aka FL clients) for modeling [13]. Based on this workflow pattern, many FL frameworks have been derived with specialized improvements in communication [108, 156, 233], optimization [104, 125, 129], robustness [44, 120, 193] and privacy [14, 32, 62]. While these fascinating improvements greatly enhance the utility of FL, they all follow a task-based interaction paradigm, in which an FL server dominates the cooperation between FL participants. In this narrow interpretation of FL, the data owner is treated more like a worker than a collaborator and performs training primarily for the benefit of the server's goals. Due to the above defects, clients have little enthusiasm to participate, and the potential for redundant training also leads to low model reusability, further diminishing the efficiency of the FL systems. This explains why current FL frameworks are more akin to private distributed modeling services rather than sustainable and privacy-preserving modeling platforms for everyone as expected.

In this paper, we try to answer the question: **Can we establish a sustainable open FL platform based on a novel reciprocal cooperation framework?** Obviously, to answer this question, it is insufficient simply study the basic concepts of FL and investigate existing FL techniques. We also need to conduct a wide survey of potential techniques that can facilitate the construction of open FL platforms. To aid understanding, Fig. 1 provides a first glimpse of two novel FL cooperation frameworks we advocated:

- **Query-based FL.** It follows a loosely-coupled cooperation framework between entities (we use "entities" instead of "participants" to emphasize equality), where any entity can freely upload their local models or retrieve models from the open repository named Model Community. There are many valuable challenges that can be explored, such as how to query for models, how to reusing the retrieved models or how to transfer knowledge from these models, how to ensure the legal compliance between different model licenses, how to protection the intelligent properties of released models (ref. Section 4).
- **Contract-based FL.** It follows a mutual choice cooperation framework, where each entity can deploy model training contracts with specialized requirements such as task modality, execution environment, model architecture and license. Meanwhile, entities holding data can choose whether to accept the contract. Research topics in this area include model pricing, model ownership verification and (ref. Section ??)

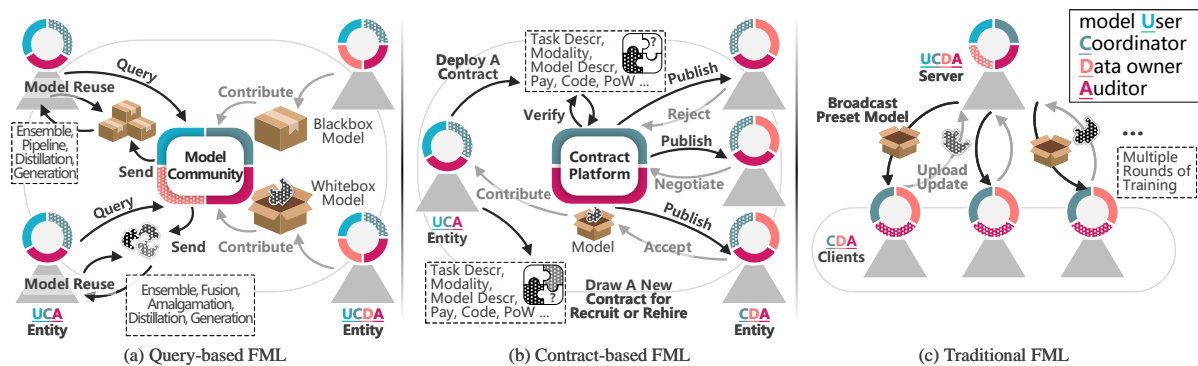


Fig. 1. A schematic diagram of three cooperation frameworks of FL. (a) (b) are the proposed open FL platforms, (c) is the traditional FL platform. Four colors correspond to four roles in [200], and colors with grid lines indicate non-essential roles.

It's worth noting that the definitions of the four roles (i.e., model user, coordinator, data owner, auditor) are adopted for compatibility with the IEEE standard [200], and our proposals are also within the scope of FML definitions. The diagram in Fig. 1(c) illustrates the workflow of traditional FL, where all FL clients are required to accept the training schedule from the FL server and perform multiple rounds of local training until the model converges. In contrast, the entities in query-based FL and contract-based are proactive in their participate. We believe that these reciprocal cooperation frameworks have the potential to expand the prevalence of FL and establish FL ecosystems.

1.1 Our Contribution

In contrast to previous surveys that primarily focused on the server-dominated cooperation framework in FL, our new survey explores the feasibility of reciprocal cooperation frameworks in FL. To the best of our knowledge, our work represents the first systematic survey in this area. The major contributions of this survey are as follows:

- We introduce the concept of open FL platforms and present two reciprocal cooperation frameworks, namely query-based FL and contract-based FL, for such platforms, along with an overview of their key features and properties.
- We investigate the query functionalities of up-to-date online model repositories and explore their feasibility for model query in query-based FL settings.
- We summarize the rights, restrictions, and enforcements of in-service model licenses and highlight the legal compliance and copyrightability issues in collaborative modeling. Additionally, we provide guidelines for selecting licenses to minimize conflicts and prevent license proliferation.
- We propose a new taxonomy to streamline the legal compliance analysis in FL studies, which is also useful for quickly identifying suitable model reusing methods for open FL platforms. A comprehensive comparison of current FL studies based on this taxonomy is surveyed.
- We analyze the requirements for model protection in the context of query-based FL and identify applicable solutions from deep intellectual property protection technologies.

The rest of this paper is organized as follows. We compare this survey to other related surveys and show our distinction in Section 2. In Section 3, we present the overview and point the limitations of traditional FL. We comprehensively explore the feasibility and challenges of query-based FL in Section 4, which includes model query (Section 4.2), model license comparison (Section 4.3.1) and selection (Section 4.3.2), copyright issues (Section 4.3.3), and analysis of license conflicts in model reusing (Section 4.3.6). In Section 4.3.4, we present our taxonomy from a model reusing perspective, and in Section 4.3.5, we summarize FL studies based on this new taxonomy. The discussion on model protection is presented in Section 4.4.

2 RELATED SURVEYS

Federated learning has become a buzzword in various fields, leading to the emergence of numerous FL studies. These works can be classified into three primary categories: FL systems design, FL applications and FL toolkits. Extensive surveys are available to summarized the advancement of federated learning, as shown in Table 1. The initial architectures and concepts for FL systems were summarized by Yang *et al.* [237]. They categorized FL into horizontal FL, vertical FL and federated transfer learning based on the distribution characteristics of data, which are written in IEEE Standard 3652.1-2020 [200, 236]. Following this, an increasing number of surveys have emerged focusing on enhancing FL system design [7, 103, 126, 128, 250]. From the algorithmic perspective, personalized FL [111, 208] aims to learn personalized models for each client to address the challenge of statistical heterogeneity [150]. Besides, the privacy-perserving computing platforms and model aggregation protocols for FL systems also been widely studied and sumariied by [48, 144, 149, 240]. Furthermore, many advanced FL architectures had been proposed, such as asynchronous [233], decentralized and blockchain-based

FL frameworks [159, 176, 266]. Given that federated learning technologies enable collaboration among distributed participants in model training and decision-making, this capability holds great promise in a wide range of application scenarios. For instance, multiple geographically distributed medical institutions can enhance medication recommendation, drug-drug interaction prediction and medical image analysis in a collaborative manner without exchanging any sensitive data [8, 173, 186, 234]. The massive real-time data generated by IoT devices in smart cities [181, 262], industries [15], vehicles [43] has also sparked interest in exploring how FL technology can be used to deliver more advanced services such as intrusion detection, anomaly detection, fraud detection and network load prediction [5, 6, 63].

As summarized in Table 1, most surveys extensively discuss the challenges of efficiency, heterogeneity, privacy in FL systems design, with the surveys from blockchain fields offering the most comprehensive review. However, except for a few blockchain-based FL studies, most of the above surveys just present the same story from slightly different angles or backgrounds, i.e. a server sets the model training task and delegate it to data holders to complete. This *server-dominated* cooperation framework is a narrow implementation of the FL systems. Therefore, this survey aims to fill the gap by investigating and surveying the associated technologies that support more open and inclusive cooperation frameworks in FL systems, where all entities, whether they own the data or not, can benefit from it. The challenges investigated in this survey are not listed in the Table 1, to the best of our knowledge, this is the first survey that focuses on the **cooperation frameworks** of FL.

Distinction of Our Survey. This survey focuses on exploring the innovative cooperation frameworks in FL, which will involve some FL concepts such as decentralized FL, blockchain-based FL, few-shot FL, ML related platforms and services but goes beyond them. In the following sections, we will distinguish our survey by highlighting the similarities and differences between these related concepts.

2.1 FL Systems

Federated learning, with its nature advantages in privacy-preserving decision sharing, has garnered significant attention in both industry and academia, leading to the rapid development of federated learning systems. The earliest attempt at the large-scale FL system was by Google, where FL was used to improve next-word prediction [77] and query suggestion [238] for Gboard applications. Subsequently, many novel FL systems have emerged to adapt to diverse federated training scenarios, such as Horizontal FL (e.g. TFF [1], FedLab [249], Felicitas [260], IBM FL [147]), Vertical FL [231] or both (e.g. FATE [142], FedML [79], PaddleFL [151], Flower [11], FedTree [122], NVFLARE [190]). Despite these frameworks covering a wide range of application scenarios, they all follow the server-dominated cooperation mechanism. This business model restricts FL to function as a collaborative modeling software, rather than an open platform that provides FL services to the public.

Unlike the FL systems mentioned above, PySyft [269] developed by OpenMined depicts a novel FL cooperation framework which is closely related to our focus. PySyft encourages data owners to share their data on a private domain server, which provides data management and privacy controls, as well as limited machine learning analysis APIs for third-party data scientists. Besides, a public network server will provide connections between data owners and data scientist, enabling datasets search and discovery for platform users. Recently, a new FL platform named PySyTFF¹ was announced. It integrates TFF and PySyft, allowing data scientists to train models under the coordination of TFF and the datasets provided by PySyft domain servers. However, even with inference controls of datasets, there is still a high security risk associated with exposing access to sensitive data on the Internet [57]. To preserve the privacy advantages of FL, in this survey, we aim to discuss an open and data-free FL platform under the scope of model-centric ML [146]. In such FL platform, every user is free to collaborate on the training of machine learning models while privacy is protected.

¹ <https://blog.openmined.org/announcing-proof-of-concept-support-for-tff-in-pysyft-0-7/>

Table 1. Summary of existing FL surveys, SYS denotes FL Systems Design, APP denotes FL Applications, SDC denotes Server-Dominated Cooperation frameworks.

Scenarios/Tasks	FL Surveys	Challenges					Contents		
		Efficiency	Heterogeneity	Privacy	Incentive	Decentralized	SYS	APP	SDC
General	Yang <i>et al.</i> [237]	✓	✓	✓	✓	✓	✓	✓	✓
	Li <i>et al.</i> 2020 [128]	✓	✓	✓		✓	✓	✓	✓
	Zhang 2021 <i>et al.</i> [250]	✓	✓	✓			✓	✓	✓
	Gupta <i>et al.</i> [73]	✓	✓	✓		✓	✓	✓	✓
	Xu <i>et al.</i> [233]	✓	✓	✓		✓	✓	✓	✓
	Li <i>et al.</i> 2021 [126]	✓	✓	✓	✓	✓	✓	✓	✓
	El <i>et al.</i> [48]			✓		✓	✓		✓
	Kulkarni <i>et al.</i> [111]	✓	✓				✓		✓
	Liu <i>et al.</i> [144]	✓		✓		✓	✓		✓
	Tan <i>et al.</i> [208]		✓				✓		✓
	Zhu <i>et al.</i> 2021 [265]		✓				✓		✓
	Ma <i>et al.</i> [150]	✓	✓	✓			✓		✓
	Aledhari <i>et al.</i> [7]	✓	✓				✓	✓	✓
	Kairouz <i>et al.</i> [103]	✓	✓	✓	✓	✓	✓	✓	✓
	AbdulRahman <i>et al.</i> [3]	✓	✓	✓	✓		✓	✓	✓
	Lim <i>et al.</i> [138]	✓	✓	✓	✓		✓	✓	✓
Healthcare	Xu <i>et al.</i> [234]	✓	✓	✓			✓	✓	✓
	Pfützner <i>et al.</i> [173]	✓	✓	✓			✓	✓	✓
	Antunes <i>et al.</i> [8]		✓	✓				✓	✓
	Rieke <i>et al.</i> [186]		✓	✓		✓	✓	✓	✓
IoT	Zhang 2022 <i>et al.</i> [262]	✓	✓				✓	✓	✓
	Boopalan <i>et al.</i> [15]	✓	✓	✓	✓	✓	✓	✓	✓
	Ramu <i>et al.</i> [181]	✓	✓	✓		✓	✓	✓	✓
	Du <i>et al.</i> [43]	✓	✓	✓	✓	✓	✓	✓	✓
Cybersecurity	Agrawal <i>et al.</i> [5]	✓	✓	✓		✓	✓	✓	✓
	Alazab <i>et al.</i> [6]			✓			✓	✓	✓
	Ghimire <i>et al.</i> [63]	✓		✓			✓	✓	✓
Blockchain	Nguyen <i>et al.</i> [159]	✓	✓	✓	✓	✓	✓	✓	✓
	Qu <i>et al.</i> [176]	✓	✓	✓	✓	✓	✓	✓	✓
	Zhu <i>et al.</i> 2022 [266]	✓	✓	✓	✓	✓	✓	✓	✓

2.2 As-a-Service Business Model

In the current context of Software-as-a-Service (SaaS) [17], there are several as-a-service cloud computing frameworks that encapsulate ML tasks as services and provides unified APIs for upper layer applications. For example, Model-as-a-Service (MaaS) [59, 140, 187, 204, 270] and Machine-Learning-as-a-Service (MLaaS) [75, 83, 110, 121, 185] encapsulate model execution and model development as services. The original concept of MaaS [59, 187] was to provide re-usable and fine-grained user interfaces and visualization tools of domain-specific models (e.g. weather model, oil spill detection model) for environmental decision support systems. Subsequently, this concept has been extended to the field of recommendation systems [270] and deep learning based systems [140, 204]. However, in contrast to the focus of this survey, the aforementioned MaaS framework does not involve any user collaboration but solely provides model inference APIs to users.

As the architectures of deep neural networks (DNNs) become increasingly complex, training and maintaining DNNs become more and more challenging [74]. To address this issue, cloud service providers have introduced MLaaS, which offers an integrated development environment as a service for constructing and operationalizing

ML workflows, aiming to reduce the computational resources required. MLaaS enables users to upload their data for training [83, 185, 263] or inference [75], freeing them from the responsibility of managing hardware resources and implementation. Most MLaaS providers adopt a pay-by-query business model, such as Google Vertex AI², Microsoft Azure Machine Learning³ and ChatGPT⁴. However, privacy protection can be compromised when users upload data to perform inference and training in the cloud. Moreover, under this model, users are not given the ability to contribute their own models to the repository or collaborate with others to enhance the diversity of available models. While there are some ongoing efforts to offer privacy-preserving MLaaS services using techniques such as Trusted Execution Environment (TEE) [75, 155] and Homomorphic Encryption [60, 83], it is worth noting that our focus is not solely on privacy. Rather, the FL framework we focus on emphasizes a collaborative framework where all entities involved have equal access to services and mutual benefits.

Recently, Kourtellis *et al.* [110] propose Federated Learning as a Service (FLaaS) that provides high-level and extensible APIs aim to enabling third-party applications to build collaborative, decentralized, privacy-preserving ML models. Jiang *te al.* [98] propose an open FL ecosystem for mobile devices, which shares a similar concept to FLaaS. However, those approach also follow the traditional server-dominated cooperation framework, which falls under the scope of previous FL surveys[103, 128, 237].

2.3 Decentralized FL

TODO: given the high scalability of modern edge computing networks, a single MEC server cannot manage to aggregate all updates offloaded from millions of devices. Therefore, there is an urgent need to develop a more decentralized FL approach without using a central server so as to solve security and scalability issues for enabling the next generation intelligent edge networks.

2.4 Blockchain-based FL

TODO:

2.5 Few-shot FL

TODO:

3 BASIC CONCEPTS OF FEDERATED LEARNING

3.1 Definition

Federated Learning [156, 200] is a collaborative machine learning modeling paradigm that enables sharing and aggregation of knowledge from multiple sources while maintaining the confidentiality of source data. Generally, in terms of task organization, there are two kinds of entities in FL systems: the server and participant. The FL server can launch a federated training task and invites participants with sufficient training data and hardware resources to contribute their local modeling results for multi-source knowledge aggregation. In practice, FL systems can be divided into two categories based on application scenarios [103]:

- Cross-device FL. In this setting, the participants are numerous end devices with relatively small dataset size, such as mobiles, IoT sensors and wearable devices, the server is hosted in the cloud. Since there is low context correlation between the data of distributed end devices and less overlapping sample ids, this setting typically falls within the scope of horizontal FL. The cross-device FL applications include: Gboard input suggestion [77, 180, 238], e-commerce recommendation [161].
- Cross-silo FL. In this setting, the participants are organizations or institutions with large amounts of well-maintained structured data, and the server is hosted by a trusted FL service providers such as FATE [142] and

² <https://cloud.google.com/vertex-ai> ³ <https://azure.microsoft.com/products/machine-learning/> ⁴ <https://chat.openai.com/chat>

NVFLARE [190]. As participants can be different departments within an organization, the data silo owned by these departments can have a large overlap in sample space and less overlap in feature space, which falls within vertical FL. The applications of cross-silo FL include federated data analysis for radiomics [130, 131, 195], epidemiology [39] and EHR [18, 85].

The allocation to the server and participants in FL is dependent on the particular application context. Furthermore, FL entities can also serve multiple functional roles to support advanced features such as privacy enhancement [14, 62, 161], participant scheduling [2, 120], model verification [197, 210] and incentive mechanisms [244]. Recall that there are four roles defined in the FL standard [200]:

- **Model User.** The FL model users can request for FL modeling services and preset the targeted task, and then establish cooperation with participants who provide training data. This role can leverage the benefits of collaborative training to improve the performance of its objective models.
- **Coordinator.** The FL coordinators are responsible for providing FL services to all FL entities. This role involves setting up communication channels with entities, initializing the execution environment of participants [75], scheduling the training and aggregation workflows for improve system efficiency, such as by alleviating the straggler effect [22, 118], optimizing data heterogeneity [2, 45] and compressing model transfer [108, 193]. Additionally, the FL coordinator provides privacy control mechanisms [14, 48, 83] for model users and authorization verification for participants to maintain the security of FL systems. Furthermore, the coordinator can hold a validation dataset for evaluate the models contributed by participants or detect potential disturbances from Byzantine attacks [192].
- **Data Owner.** The FL data owners are knowledge contributors of FL systems, they collect and desentize raw data to maintain a local dataset for federated training. Although they have full authority of data processing and modeling, they cannot share the raw data due to privacy concerns. To address these concerns, de-identification [4] and differential privacy [47] techniques can be applied to meet privacy budgets as required by privacy policies.
- **Auditor.** The FL auditors are responsible for formulating privacy control policies and establishing supervisory mechanisms that ensure the training process is compliant with data protection regulations (e.g. HIPAA [4], GDPR([217])) and preventing potential privacy breaches for both model users and data owners. Especially in FL, the latent knowledge in models can potentially reveal the sensitive information of training data [101, 225, 267], making it crucial for auditors to scrutinize the model transmission [135, 226] and verify the ownership of models [197, 210].

Fig. 2 illustrates the typical architecture of FL systems, which as a distributed modeling toolkits consists of server part and client part. In general FL setting, the server part is the central aggregator installed in a trusted cloud environment, while the client part of software can operate in different operating environments of client devices. The server and clients are connected via Internet and typically with the help of Remote Procedure Call (RPC) interface for coordinating [1, 11, 79, 142, 260]. We use four colors to represent the four FL roles and the colors with grid lines indicate non-essential roles. For example, in Fig. 2, the UCDA server takes on the roles of model user, coordinator and auditor in traditional FL. However, it is no necessary to hold training data or validation data, so the role of data owner is non-essential. To illustrate the workflow of traditional FL, we leverage the vanilla FL framework Federated Averaging (FedAvg) [13, 156] as an example.

First, the FL server pre-defines the objective modeling task and initializes the server process. Secondly, the coordinator in server-side specifies a preset global model and the operational parameters. Thirdly, the coordinator discovers the availability of clients' FL services, boardcasts the global model and training config to them. The training config contains bath size, local epoch round, optimizer parameters and so on. Then, the coordinator will wait for the trained results contributed by the coordinator in clients-side and drop those clients with network problems. Finally, the server aggregates the trained resultes received from various clients into the global model

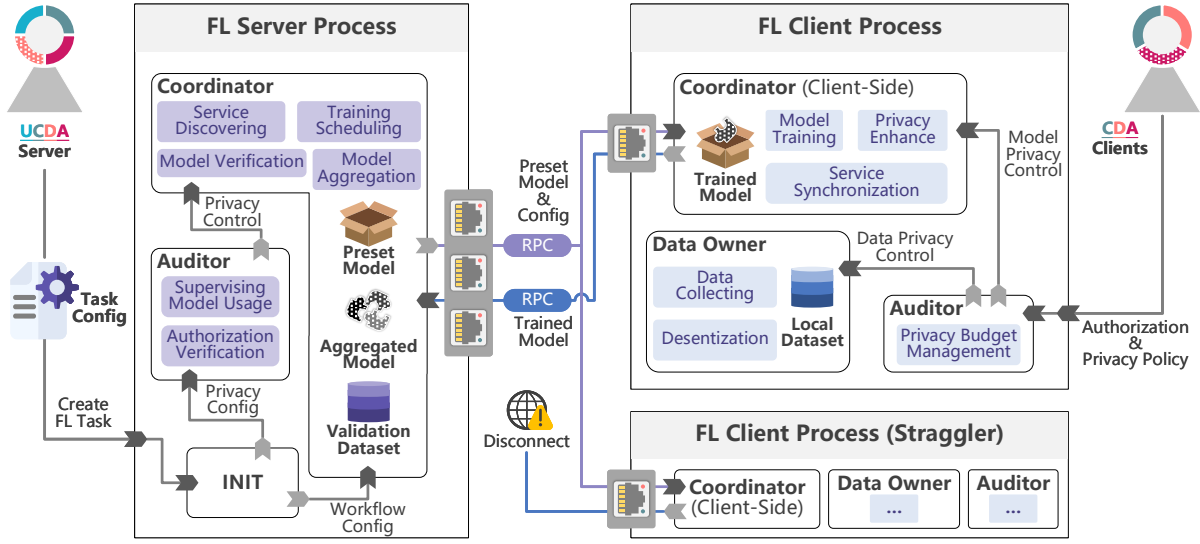


Fig. 2. An overview of traditional FL systems. (U: model User, C: Coordinator, D: Data owner, A: Auditor)

and begins a new round based on this aggregated global model. The aggregation strategy adopted in FedAvg is the weighted model parameters based on the size of local dataset, which means the global objective of FL can be regarded as a joint objective function of clients. By this way, the FL server can learn a generalized global model by jointly optimizing all local optimization objectives and incorporating the latent knowledge from the local models. Although the auditor component was not included in earlier FedAvg, it play an important role in the later business-ready FL frameworks [142, 190, 269].

However, in comparing FedAvg workflow described above with Fig. 2, it is easy to notice that the client part has been excluded. This is because we are elaborating from a server-side perspective, which is usual way FL is presented [19, 127, 156]. Actually, the underlying reason is that in traditional FL, the client-side process is tightly coupled with server-side process, and there is no alternative for clients other than to either accept or reject the training scheduling from the server wholesale. So the clients are not considered as an autonomous entities but rather work as subordinates to server. In this server-dominant cooperation framework, the benefits and autonomy of clients are compromised, which hinders their enthusiasm to participate in FL network and subsequently limits the applicability of FL. From this perspective, we summarize the limitations of traditional FL in the next section, which motivates us to explore more innovative sustainable FL cooperation frameworks.

3.2 Limitations of Traditional FL

Previous surveys [6, 103, 128, 159, 208, 237, 262, 266] has extensively discussed the challenges in FL systems from various aspects. However, the cooperation mechanism of FL systems has been overlooked because almost all mainstream FL frameworks follow the FL prototype [156], which shape the form of current FL frameworks: a modeling software. We summarize three inherent limitations of traditional FL cooperation mechanism: (1) **Server-client Coupling**, (2) **Low Model Reusability**, (3) **Non-public**.

3.2.1 Server-client Coupling. The tightly-coupled server-client design is a major limitation of FL systems. From the perspective of FL service providers, adapting the programs to heterogeneous client hardware and software components, such as various operating and database systems, processor and storage architectures, communication

protocols, energy constraints and data licenses, is a challenging task that significantly increases the complexity of the FL system.

On the other hand, the invasive software deploy mode compromises the integrity of client environments and expose them to new privacy risks. Specifically, the coordinator components (client-side) pushed by the server may not offer demanded privacy control mechanisms [19, 156, 249], or cause resource depletion on client-side [13, 31, 161], or even piggyback malicious executable codes [119]. So the auditor role of client is non-essential as depicted in Fig. 2, not only because the client maybe lacks a corresponding policy for FL training, but also because its privacy is not completely under its control. Likewise, the malicious clients can also exploit the vulnerability in the aggregation strategy to corrupt the FL training process [16, 51, 167, 192] or insert backdoors [10, 218]. In addition, the unstable network environment can drive clients to drop out from training (i.e. straggler effect), thereby reducing system efficiency [167, 184]. Therefore, the server-client coupling design of traditional FL systems make them susceptible to unpredictable runtime environments, leading to system vulnerability and low reliability.

3.2.2 Low Model Reusability. The traditional FL scheduling follows a task-centric manner and terminates once the training reaches a preset number of rounds or meets target metrics on global model set by FL server [13]. As a result, only FL server can guarantee having the latest global model after the task is terminated. This ad-hoc modeling paradigm results in low model reusability and transportability. For example, if a client who participated in the previous training turn wants to continue training, they can only start the task from scratch unless they have the up-to-date global model. Since only FL server is able to maintain the complete modeling trajectory, it is difficult for the client to roll back the training itself to eliminate the potential privacy risk. Furthermore, the non-deliverable scheduling mechanism of FL tasks also hinders inter-task model reuse, which leads to unnecessary wasted energy and time on participants that have been involved in similar tasks.

3.2.3 Non-public. As we mention in Sec. 2.1, except PySyft [269], the application scenarios of mainstream FL frameworks [1, 11, 19, 79, 142, 147, 190, 249] aim to provide private collaborative ML training service, and there is no any accessible FL platform for the public. Although there have been real-world deployment practices of FL for the public with scales of millions [13] and billions [161], these have been carried out only by tech giants with a massive base of active users. For an individual user, there is no practical way to organize such a large-scale FL training network.

But in fact, due to the limitations in the cooperation mechanism mentioned above, data owners are not sufficiently motivated to participate in this server-take-all FL training even if it is public accessible. Therefore, the cornerstone of building a sustainable open FL platform is to establish a reciprocal FL cooperation framework, followed by corresponding multi-source knowledge aggregation strategies, which we discuss in the following sections.

4 QUERY-BASED FEDERATED LEARNING

4.1 Overview

Let us continue by establish a sustainable open FL platform based on a query-based cooperation framework. An overview of this platform is presented in Fig. 3, the design philosophy behind this framework is to break the coupling between FL server and clients. In the query-based FL systems, all traditional FL roles and components are maintained on an open model repository called Model Community. The Model Community provides a one-stop ML models redistribution and reuse service, including model indexing, automatic batch model reuse, license management, privacy control and so on. In addition to large-scale pretrained models like BERT [41], BLOOM [194] with great generalization abilities, we also encourage individuals to upload their task-specific models trained on limited domain data to boost the knowledge mining within models [242]. The derivatives of knowledge

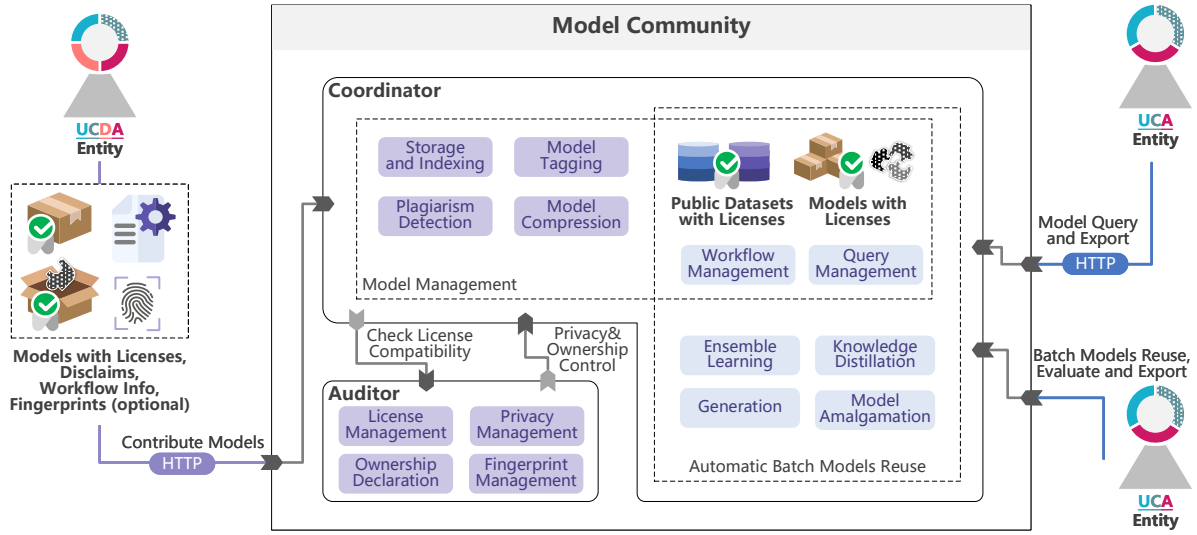


Fig. 3. An overview of query-based FL systems. (U: model User, C: Coordinator, D: Data owner, A: Auditor)

mining can learn representations from multiple domains, resulting in more promising performance that can be evaluated by platform users. Furthermore, the contributors can release models under applicable licenses, granting them distribution control and legal protection of their intellectual property (IP). In summary, the properties of query-based FL are: (1) **Model Agnostic**, as there are no restrictions on the types and architectures of the models uploaded by users; (2) **Contactless**, as communication channels need not be maintained; (3) **Community-powered**, whereby sharing models enriches the entire community.

Actually, we aim to advocate a novel SaaS [17] ML platform with automatic model reuse integrated, which has potential to leverage the transportability of models to address previously unexplored ML problems. Due to the high computational demands of deep learning, current ML platforms primarily concentrate on computing, for example, MaaS, MLaaS, FLaaS provide ML models deployment and development services to handle user-specified tasks. (Section 2.2). On the other hand, there are several ML platforms provide open model search and download services. So, can we leverage off-the-shelf open model platforms to build a query-based FL system? Unfortunately, these platforms are designed solely for sharing and are not suitable for more advanced functionalities such as model ensemble [90] and knowledge distillation [84], we will explain the reasons in the following section.

4.2 How to Query for Models

To establish a query-based FL platform, the first thing that comes to mind is how to query for models. Unlike traditional ML model sharing repositories that mainly query for a specific model by name, it requires an efficiency approach to export a batch of target models that ready for ensemble or distillation. We summarized the filter conditions of existing DNNs sharing repositories in Table 2. The prevailing method for querying models involves searching for the desired model by its name, datasets used, associated tasks. To illustrate, one might search for the model name GPT [178], models trained on the MNIST dataset [114], or models capable of performing image segmentation tasks. However, this model retrieval method requires the users have a strong priori knowledge in data science, thus raising the barrier for knowledge mining within models. For example, there is no effective way

Table 2. Filter conditions and characteristics of DNNs repositories. ✓: Supported, ✗: Unsupported, !: Information provided but unsearchable, listed in descending order by number of models.

	DS Name	Model Architecture	Modality/Task	Tag	License	Input-Output	Batch Export	# of Models
Hugging Face ⁵	✓	✓	✓	✓	✓	!	✗	133,641
Model Zoo ⁶	✓	✓	✓	✓	✗	✗	✗	3,426
Tensorflow Hub ⁷	✓	✓	✓	✓	!	!	✗	1,356
NVIDIA NGC ⁸	!	✓	✓	✓	!	!	✗	527
OpenVINO ⁹	!	✓	✓	✗	!	!	✓	278
Pytorch Hub ¹⁰	!	✓	✗	✗	✗	!	✗	49

to acquire a batch of image classification models that contains the knowledge of *lesser panda* for further distillation. A compromise solution is to manually search the schema of each dataset one-by-one and subsequently search for models trained on those datasets.

Additionally, as shown in Table. 2, most DNNs repositories are simply list the description of input/output (e.g., NVIDIA NGC, OpenVINO) or even just present the source codes (e.g., Tensorflow Hub, Pytorch Hub), This lack of unified convention for model input/output poses a challenge for query-based FL. Besides, most of DNNs repositories do not enable querying models by licenses, resulting in the cumbersome task of individually handling model licenses and ensuring compatibility among different licenses. Hence, it is imperative to reconsider the design of DNN repositories to enable quick identification of readily reusable models for model knowledge mining. We further suggest following filter conditions for query-based FL.

4.2.1 Data Description. Similar with the data heterogeneous challenges in FL [123]. The local datasets of contributors have varying quality and contain intractable biases, imbalances and noises that can be attributed to the natural characteristics of demographic or improper data collection mechanisms [39]. Besides, label errors pervasive even in open datasets [162]. So, in addition to searching for domain-specific datasets based on their data descriptions, we are also seeking such descriptions for the purpose of future traceability and debugging. The data description can consist of statistical analysis results or the visualization diagrams that used to profile the data distribution [131] and complementary provenance information.

4.2.2 Workflow and History. The process of building an ML model is iterative, involving repeated hyperparameter tuning and architecture exploration, resulting in abundant workflow and historical trajectory data. This information includes pipelines, model structures, hyperparameter values for pre-training and fine-tuning, test metrics, and results. These data can be useful in filtering models that meet specific requirements, such as those with data standardization in preprocessing or evaluated using mean average precision (mAP). Instead of manually saving and uploading the logs and configuration files, a more efficient method is to leverage ML workflow management tools [215], such as MLflow¹¹ and Neptune¹², to automatically track and store the ML workflow during model building process. This information can also assist in identifying potential model plagiarism within the model community. Additionally, to ensure that the computational consumption of models is within budget, the Deep Learning Profiler¹³ can be leveraged to generate a report that shows the FLOPS and bandwidth requirements.

4.2.3 Software Dependency. ML models are software that depend on underlying ML libraries, so it is important to declare the dependencies of the model to analyze software compatibility between batches of models. For instance, resource-constrained devices may need to trim down the list of software-dependent libraries to meet limited storage space requirements [38]. In some cases, contributed models may rely on other models as dependencies.

⁵ <https://huggingface.co>

⁶ <https://modelzoo.co/>

⁷ <https://tfhub.dev/>

⁸ <https://catalog.ngc.nvidia.com/models>

⁹ https://docs.openvino.ai/latest/model_zoo.html

¹⁰ <https://pytorch.org/hub/>

¹¹ <https://mlflow.org>

¹² <https://neptune.ai>

¹³ <https://docs.nvidia.com/deeplearning/frameworks/dlprof-user-guide/index.html>

For example, Fast R-CNN [64] uses VGG16 [199] as its backbone. It is crucial to release this information for further model license compatibility analysis.

The aforementioned filter conditions provide comprehensive coverage of the ML modeling process. However, there are additional requirements depending on the reuse mechanisms of the model retrieval side. For example, FedAvg [156] aggregates the local models weights element-wise, which requires full access to the models. In contrast, MoE with a gating network [90] only ensembles a batch of model outputs, so the individual models can remain blackboxes in this scenario. So, in the context of software licenses or model licenses, the batch models reused by FedAvg should be released as source code, while those reused by MoE can be released as binary object code (static linking). The above distinction is crucial for ensuring that model reuse results meet the legal framework, and this has been overlooked in traditional FL. We will expand on this topic in the following section.

4.3 How to Reuse Batch of Models

Once we have acquired a certain number of models that can contribute to the new target task, the next step is to reuse the knowledge of these pre-trained models, i.e., transfer their knowledge from source domain to the target domain [166]. However, before deciding on how to reuse the model, it is important to ensure that the necessary legal rights and permissions have been obtained. This may involve reviewing the terms and conditions of the licenses under which the models were originally released or obtaining permission from the original creators or copyright holders. Therefore, in this section, we will not focus on the technical details of how to reuse models, which is already covered by many related surveys, such as Transfer Learning [166], Ensemble Learning [264], Domain Adaptation [222], Knowledge Distillation [221], Deep Generative Models [20] and Model Fusion [93]. Furthermore, the specific model reuse technique or techniques used is at the user's discretion, and the query-based FL platform we advocate is not bound or restricted to any particular model reuse algorithm. Innovatively, we study how to reuse batch of models, from the perspective of **legal compliance**.

The machine learning community benefits from the openness of ideas and code, and many high-impact ML conferences and journals encourage authors to publish their source code and dataset to research platforms like Papers With Code¹⁴ and Code Ocean¹⁵ to increase exposure and facilitate reproducibility. To restrict the use of ML techniques for unethical purposes (i.e. Deepfakes [158]) and protect the IP of creators, models are typically published under a license agreed upon by the licensor. Here, we summarize the licenses, granted rights, restrictions and enforcements for ML models posted on Hugging Face in Table. 3.

4.3.1 Model Licensing Forms. ML models are licensed in three main forms: as software (e.g. Apache, MIT, GPL), as a model (e.g. OpenRAIL), and as content/database (e.g. CC-BY, PDDL). The reason for the mixed use of licenses is the ambiguity in the dependency relationship between the code, model, and data. ML models can be released with reproducible code and be considered as a component of software. So many open software licenses are naturally deferred for licensing of models. The most popular license is Apache-2.0, which is a permissive open software license that allows the freedom to make derivative works. However, the model building process also relies on a massive amount of data [113] that may be licensed under different licenses, which can lead to license conflicts. A practical example is BERT [41], which was published under the Apache-2.0 license but pre-trained on English Wikipedia documents that are licensed under CC BY-SA 3.0. This changing of license violates the requirement of the CC BY-SA 3.0, which states that any contribution must be distributed under the **same license** as the original work.

From the perspective of content and database licensing, some word embedding models, such as GloVe [170], compute vector representations of words based on licensed open linguistic resources. These representations can be regarded as a translation of corpus and fall under the license of the original linguistic resources. A more complex scenario arises when the model is fine-tuned with other data that has a different license, for example,

¹⁴ <https://paperswithcode.com> ¹⁵ <https://codeocean.com>

fine-tune RoBERTa [143] (MIT license) with SQuAD2 [179] (CC BY 4.0). The resulting model can be interpreted as both derived works and combined works.

Not only limited to protecting the IP and controlling the diffusion of ideas, but AI companies and researchers are also concerned about licensees using their models for unethical purposes [9, 102, 248], which is not restricted by traditional licenses based on the context of software and content. We can infer the concerns of the inventors of GPT-2 [178] about the unethical use of the model from its modified MIT license, which states, *We don't claim ownership of the content you create with GPT-2, so it is yours to do with as you please. We only ask that you use GPT-2 responsibly and clearly indicate your content was created using GPT-2.* However, such a statement lacks legal enforcement, and users may avoid accountability by convincing themselves that despite their efforts to minimize harm, they could not predict the AI artifact they generated would be used for harmful purposes. Besides, the original licensing frameworks for software and content (e.g. MIT, CC BY) are not well suited to the data-driven ML. Many ML operations, such as training, fine-tuning, inference, and distillation, are not explicitly defined in traditional software and content licenses, leaving a potential legal loophole for licensees.

To address the unique challenges and considerations surrounding the use and distribution of ML models, several specific licenses for ML models have been proposed. The CreativeML OpenRAIL-M license, proposed by Responsible AI [36], is the most popular model-specific license on Hugging Face and enables legally enforceable responsible use. By accepting this license, licensees must adhere to the use-based restrictions stated by the licensor, and these restrictions must also apply to derivative works. With a multitude of different model licenses available, it becomes a challenging and tedious task to reuse them in bulk. It is therefore imperative to establish guidelines for selecting a license for models that are ready for query-based FL.

4.3.2 License Choosing Preferences. In query-based FL, the model community automatically reuses models contributed by users, which raises unique concerns about licensing of models:

- A model license ready for open FL platforms should allow the **modification, combination and redistribution** of original works and any derived works; and
- **Sublicensing** right should be granted to lubricate the republication of derived works resulting from knowledge mining; note
- Some licenses enforce the source of the derived works to be **disclosed** and prohibit their **commercial use**, which hinders model selling [30]; and
- Some licenses are **copyleft** (marked with * in Table. 3), which means the derivatives must be licensed under the same license or a compatible one, leading to potential license conflicts and proliferation [65]; last
- All granted rights are preferably **irrevocable** by the licensors [182].

Besides, it is important to consider the licensing of two other components when building and reusing models: data and algorithms, which may have entirely different license terms. Here, we present several strategies for selecting licenses in query-based FL to minimize conflicts.

Preferences for Datasets or Databases: CC0-1.0, ODC-By > CC BY > C-UDA > LGPL-LR.

Our recommended licenses for training datasets and databases for query-based FL are CC0-1.0, ODC-By, and CC BY. CC BY-4.0 is preferred due to the grant of *Sui Generis Database Rights (Art.1c)*. CC0-1.0 and ODC-By are more permissive than CC BY since they do not require licensees to disclose any modifications made to the dataset or database, and CC0-1.0 does not require the declaration of the original license. Although these licenses do not explicitly grant sublicensing rights, they provide an automatic licensing policy for downstream recipients.

C-UDA is an alternative license that grants sublicensing rights, but it includes additional usage restrictions that limit its application to computational use only, which indicates commercial use is not allowed. To avoid license proliferation, it is not recommended to use any data under copyleft licenses for building models, as the resulted models could be seen as remixing and making derivatives of the original datasets, leading to potential conflicts between licenses. Among them, LGPL-LR is an exception because it contains an exemption clause for *work that*

Table 3. Licenses for ML models available on Hugging Face with a focus on their rights, restrictions and enforcements, grouped by free software licenses, AI model licenses, free content or database licenses in descending order of number of models (GPL, BSD, LGPL, CC licenses with unspecified versions are excluded, the similar revisions are merged). ✓: Permitted or Required, ✗: Not Permitted or Not Required, !: Not Explicitly Permitted, *: Copyleft License

Licenses	Modify / Merge	Redistribution	Sublicensing	Commercial Use	Patent Use	Trademark Use	State Changes	Disclose Source	Responsible-use Restrictions	License/Disclaimer Preservation	# of Models	Licensed Materials / Remarks
Apache-2.0	✓	✓	✓	✓	✓	✗	✓	✗	✗	✓	23,519	BERT [41]
MIT	✓	✓	✓	✓	!	!	✗	✗	✗	✓	9,605	GPT-2 [178]
AFL-3.0	✓	✓	✓	✓	✓	!	✓	✗	✗	✓	1,561	Italian-Legal-BERT [137]
*GPL-3.0	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓	404	CKIP BERT Chinese
Artistic-2.0	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	331	Include original source
BSD-3-Clause&-Clear	✓	✓	✓	✓	!	!	✗	✗	✗	✓	209	CodeGen [160]/ A MIT-style license
WTFPL-2.0	✓	✓	!	✓	!	!	✗	✗	✗	✗	131	A MIT-style permissive license
*AGPL-3.0	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓	96	Distributed under AGPL only
Unlicense	✓	✓	!	✓	!	!	✗	✗	✗	✗	90	A MIT-style permissive license
BSL-1.0	✓	✓	✓	✓	!	!	✗	✗	✗	✓	60	A MIT-style permissive license
*GPL-2.0	✓	✓	✗	✓	!	!	✓	✓	✗	✓	34	Not compatible with GPL-3.0
BSD-2-Clause	✓	✓	✓	✓	!	!	✗	✗	✗	✓	34	A MIT-style permissive license
*LGPL-2.1&3.0	✓	✓	✗	✓	!	!	✓	✓	✗	✓	25	For software libraries
*OSL-3.0	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓	22	Linking is not derivative work
ECL-2.0	✓	✓	✓	✓	✓	✗	✓	✗	✗	✓	12	For education communities
*MPL-2.0	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓	9	State changes under MPL only
ISC	✓	✓	!	✓	!	!	✗	✗	✗	✓	8	MIT-style license w/o sublicense
Zlib	✓	✓	!	✓	!	!	✗	✗	✗	✓	8	Rename if modified
*Ms-PL	✓	✓	✓	✓	✓	✗	✗	✗	✗	✓	7	Weak copyleft license
*EPL-1.0&2.0	✓	✓	✓	✓	✓	!	✗	✓	✗	✓	6	Can link proprietary license code
NCSA	✓	✓	✓	✓	!	✗	✗	✗	✗	✓	4	Include full text of license
PostgreSQL	✓	✓	!	✓	!	!	✗	✗	✗	✓	2	A MIT-style license
OFL-1.1	✓	✓	✗	✓	!	!	✗	✗	✗	✓	2	For font software
*EUPL-1.1	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓	1	License of EU covers SaaS
LPPL-1.3c	✓	✓	✓	✓	!	✗	✓	✓	✗	✓	1	Covering stewardship transfer
CreativeML-OpenRAIL-M	✓	✓	✓	✓	✓	✗	✓	✗	✓	✓	3,590	Stable Diffusions v1 [188]
OpenRAIL	✓	✓	✓	✓	✓	✗	✓	✗	✓	✓	2,393	ControlNet [257]
BigScience-BLOOM-RAIL-1.0	✓	✓	✓	✓	✓	✗	✓	✗	✓	✓	196	BLOOM [194]
BigScience-OpenRAIL-M	>Same as BigScience-BLOOM-RAIL-1.0										155	A general version of 1.0
OpenRAIL++	>Same as CreativeML-OpenRAIL-M										72	Stable Diffusion v2 [188]
OPT-175B	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓	≈ 66	OPT LLM [261]
SEER	>Same as OPT-175B, ban on reverse-engineer										/	SEER Vision Model [69]
CC-BY-4.0&3.0&2.5&2.0	✓	✓	!	✓	✗	✗	✓	✗	✗	✓	1,740	RoBERTa-SQuAD2.0 [179]
*CC-BY-SA-4.0&3.0	✓	✓	✗	✓	✗	✗	✓	✓	✗	✓	590	LEGAL-BERT [23]
*CC-BY-NC-SA-4.0&3.0	✓	✓	✗	✗	✗	✗	✓	✓	✗	✓	556	LayoutLMv3 [87]
CC-BY-NC-4.0&3.0&2.0	✓	✓	!	✗	✗	✗	✓	✗	✗	✓	499	GALACTICA [209]
CC0-1.0	✓	✓	!	✓	✗	✗	✗	✗	✗	✗	165	BlueBERT [169]
CC-BY-NC-ND-4.0&3.0	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓	21	NonCommercial, NoDerivatives
PDDL	✓	✓	✗	✓	✗	✗	✗	✗	✗	✗	16	Database-specific license
C-UDA	✓	✓	✓	✗	!	!	✗	✗	✓	✓	13	Data for computational use only
*LGPL-LR	✓	✓	✗	✓	!	!	✓	✓	✗	✓	12	LGPL for linguistic resources
*GFDL	>Same as GPL, a free document license										12	txtai-wikipedia
CC-BY-ND-4.0	✓	✗	✗	✓	✗	✗	✓	✗	✗	✓	11	Disallow making derivatives
ODC-By	✓	✓	✗	✓	✗	✗	✗	✗	✗	✓	7	Automatic relicensing
*ODbL	✓	✓	✗	✓	✗	✗	✓	✓	✗	✓	6	Automatic relicensing

uses the Linguistic Resource (Art.3), which is suitable for end-to-end training, fine-tuning, and embedding. But it is worth noting that the embedded representations may be considered *translated straightforwardly into another language* (Art.0), which falls within the scope of LGPL-LR license.

An example of license proliferation is LEGAL-BERT [23], which was trained on data from the Case Law Access Project ¹⁶ (licensed under CC BY-SA 4.0). This restricts LEGAL-BERT to the same license and prevents further model reusing on datasets or models licensed under incompatible copyleft licenses, such as LGPL-LR and GPL.

Preferences for Software: Apache-2.0, AFL-3.0, Artistic-2.0, ECL-2.0 > MIT, BSD-3-Clause&-Clear, BSL-1.0, BSD-2-Clause, NCSA ≈ Ms-PL > WTFPL-2.0, Unlicense, ISC, Zlib, PostgreSQL.

Our top recommended software licenses for training and reusing models are Apache, AFL, Artistic, and ECL. These permissive licenses allow modification and sublicensing, explicitly grant the use of patents and permit commercial use, and do not require the disclosure of the source code but only the stating of any changes made to the original work.

The next set of recommendations are MIT, BSD, BSL, and NCSA. These licenses do not explicitly grant patent rights but instead, do not require the stating of modifications made to the original work, thus avoiding the tedious task of tracking model reusing or incremental training procedures. Ms-PL offers two advantages simultaneously, but it is a weak copyleft license that requires the modified source code to also be licensed under Ms-PL, and the derivative object code to be compliant with a license compatible with Ms-PL. However, open software licenses do not provide a clear definition for software-generated outputs such as models. It is unclear whether models are considered a portion of the software, and whether they are in source code form or object code form. This ambiguity makes it difficult to determine the applicable clauses for models.

Our latest recommended licenses include WTFPL, Unlicense, ISC, Zlib, and PostgreSQL. These licenses are very permissive and allow almost anything without restrictions. However, it's important to note that these licenses do not explicitly grant sublicensing rights and patent, which can lead to ambiguity in interpreting the license clauses. For the avoidance of doubt, copyleft licenses such as GPL, AGPL, LGPL, OSL, MPL, EPL, and EUPL are not recommended, despite the loophole that they do not have a specific definition for models. Furthermore, although some of those copyleft licenses can be made compliant with others, we recommend isolating the software license from the resulting models to preserve the freedom to use the models further (e.g., close-source or relicense).

Preferences for Models: Apache-2.0, AFL-3.0, Artistic-2.0, ECL-2.0 > OpenRAIL and its derivatives

There are two recommended choices for model licenses for query-based FL. The first is permissive open software licenses like Apache, AFL, Artistic, and ECL. The second is open model-specific licenses like OpenRAIL and its derivatives. As shown in Table 3, the main difference between the two choices is that OpenRAIL offers additional user behavioral restriction clauses and enforces these restrictions via a copyleft-style agreement. For example, CreativeML OpenRAIL-M license claims *Therefore You cannot use the Model and the Derivatives of the Model for the specified restricted uses ... You shall require all of Your users who use the Model or a Derivative of the Model to comply with the terms of this paragraph*. The restricted uses include actions that could cause harm, provide medical advice, generate or disseminate verifiably false information, and more. So, the model owners may adopt these licenses for the purpose of responsible model use.

However, in practice, such discrimination of user behavior cannot completely guarantee that the models will not be misused, and may potentially compromise the openness of the models [70, 171]. The user behavioral restrictions in licenses can be compared to manufacturers prohibiting the use of their laptops for hacking, and furthermore, the vendors can be held jointly and severally liable for any future violations, which is unreasonable and may lead to the licensed materials becoming closed source. Furthermore, to enable remote control for the responsible use of AI, CreativeML OpenRAIL-M includes the clause *You shall undertake reasonable efforts to use the latest version of the Model*, which requires licensees to keep up with the updates of the original work and may render their prior development efforts useless. Therefore, traditional permissive licenses, which follow worse-is-better design philosophy [56], are good choices for model licensing in query-based FL, as they promote openness and facilitate the sharing of publicly contributed models.

¹⁶ <https://case.law>

The remaining model licenses, OPT-175B and SEER, are proprietary licenses that allow licensees to use and reproduce the licensed models subject to certain restrictions. Given that their granted rights are revocable, we do not recommend using any content of works and derivatives under these licenses in query-based FL.

It is worth noting that the above discussion only deals with the licenses of inputs for open FL platforms, which aim to provide legal compliance and freedom of outputs as much as possible, but does not involve the copyright issue for the outputs. In fact, except for some public domain dedication licenses like CC0-1.0, PDDL, Unlicense, and WTFPL, most licenses only grant non-exclusive rights for use and distribution, and the original copyright and attribution are retained by the licensors. Whether the reused models are copyrightable is crucial for incentivizing model sharing and mining, so we will elaborate on this topic in the next section.

4.3.3 Copyright of Reused Models. Software and computer code are indisputably copyrightable, but what about computer-generated content such as distillation and ensembles of models? The copyrightable of a computer-generated work is controversial, which may depend on such as the level of creativity and originality and *presence of at least minimal human creative effort at the time the work is produced* [163]. According to this definition, programmers who engage in model design and training meet the threshold requirements of copyrightability and own the copyright of the model. That is why all the licenses listed in Table 3 contain claims of copyright. But the debating point is whether the reused models also copyrightable? Unfortunately, there is no universal answer to this question as it can depend on the specific case and fact pattern. The crux is whether the efforts involved in reusing the model meet the minimum creative requirements for copyrightability. For example, if we simply stack two models end-to-end, it may not meet the threshold for copyrightability. However, if we improve a basis model using distilled knowledge from other domains, that would be more likely to meet the requirements for copyrightability. Except for copyrightability, the authorship of a reused model is also open to controversy, as it depends on whose *original intellectual conceptions* the work embodies, and joint authorship is also possible [81].

The determination of copyrightability and authorship of computer-generated content is an open issue that needs to be addressed through corresponding legislation [81, 154, 163]. The possible answers to the question of authorship of computer-generated models are model authors, model users, data owners, any combination of them, or no one [81]. Licensors can also make efforts to clarify this issue by including relevant claims in their licenses. For example, the license of Stable Diffusion [188] explicitly states that *Licensor claims no rights in the Output You generate using the Model*. Similarly, ChatGPT¹⁷, even though it is a proprietary software of OpenAI company, its sharing & publication policy¹⁸ states *The published content is attributed to your name or company*. Therefore, we are free to use their generated content for model reusing and can claim the copyright of reused models. On the contrary, the licenses of OPT [261] and SEER [69] do not grant any copyright for the data produced by the licensed software. Given that, we should avoid using their derivatives and generated content in query-based FL to prevent copyright infringement. Once we obtain the right to relicense the modification models, the choice of a new license depends on the application scenario of models. We provide a flowchart in Fig. 4(a) to guide license selection. For now, we have provided a comprehensive perspective and suggestions regarding the regulations and legal issues related to batch model reusing with only one piece missing: the definition of terms and corresponding clauses for different reusing mechanisms in different licenses. The terms definition for model reusing in different licenses is a novel and interesting issue that is rarely discussed. For example, interpreting model reusing as creating derivatives or combinations would involve different clauses in the licenses. To provide a better understanding of these implications, let's first provide an overview of typical model reuse mechanisms.

4.3.4 Batch Model Reuse Mechanisms. Instead of summarizing the batch model reuse mechanisms from a technological and algorithmic aspect, we propose grouping these mechanisms based on the classification of their resulting outputs for ease of justifying license clauses. As shown in Fig. 4(b), there are four categories of batch

¹⁷ <https://openai.com/blog/chatgpt> ¹⁸ <https://openai.com/policies/sharing-publication-policy>

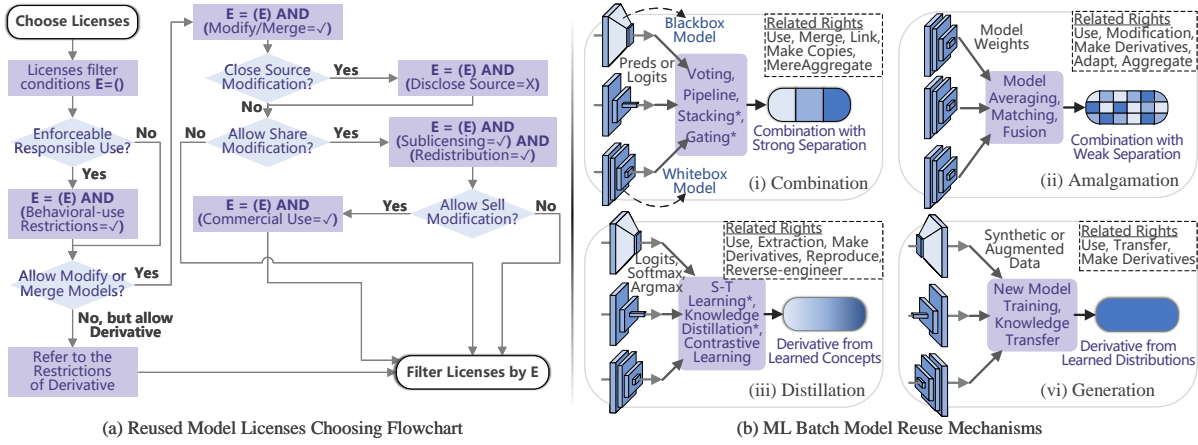


Fig. 4. flowchart

model reuse mechanisms: **Combination, Amalgamation, Distillation, and Generation**, each resulting in different forms of outputs and may correspond to different regulations in licenses.

Combination [264] is a straightforward way to reuse batch of models (aka base learners), in which multiple models jointly contribute to the output by combination strategies such as averaging, voting, learning [90, 228]. For regression estimates, averaging can improve the generalization by taking the mean of the outputs of all weak learners in a population. Additionally, the outputs of each learner can be weighted by extra parameters [172], which can be determined by stacking estimators [228], Bayes approach [35] or backpropagation of gating networks [90]. Voting is a workaround for classification tasks and also applicable for stacking and gating. Both stacking and gating rely on an additional holdout or validation dataset for calculating extra parameters, marked as * in Fig. 4(b). The difference is that gating can adapt the weights of each model's estimation based on the inputs, providing better generalizability performance of the combined model.

There are many **advantages** of combination mechanisms from the perspective of FL. First, the input spaces of base models can be unaligned, which is ideal for the scenario of vertical FL [231] where each client may have inconsistent features in their data. Secondly, especially for query-based FL, it can simultaneously support multiple types and heterogeneous models, which means that it does not rely on any prior assumptions of the models, such as whether they are DNNs or decision trees, released with weights (whitebox) or binary forms (blackbox). Thirdly, the tasks of models can be different if we pipeline the base models end-to-end, which is usually overlooked as a combination mechanism of models. Pipelining can fully leverage the transferability of models to solve previously unexplored ML problems. For instance, Gao *et al.* [58] proposed a zero-shot dense retrieval system named HyDE by pipelining a natural language generation (NLG) model [165] and a natural language understanding (NLU) model [89]. The generated content, which may lack factual grounding, from the NLG model is used as query embeddings to facilitate real document retrieval by the NLU model. Through query-based FL, we can query a vicarious NLG model for a novel scenario, such as ProGen [153] for protein sequences generation, and quickly adapt this system to proteomics. Not limited to that, we can query a batch of NLG models by a well-chosen filter condition and then combine models through averaging or gating to significantly expand the exploration space for knowledge discovery. Lastly, the combined models have strong separation from each other, meaning that we can add or remove a batch of models without significant changes to the remaining ones. Meanwhile, combination mechanisms do not rely on the transparency of models and support blackbox sharing. Thus, the

base model can establish loose connections with other models only through run scripts, providing revocability of such combination and circumvention of the restrictions of licenses.

On the other hand, instead of being treated as a challenge for FL [150], the statistical heterogeneity and model heterogeneity nature of these crowdsourced models can actually enrich population diversity, which is crucial for creating a good ensemble [152, 164]. **However**, the storage consumption of combined models increases linearly with the number of base learners, which can deplete the communication resources of a model distribution network. Therefore, alternative approaches are to amalgamate or merge multiple models into a new consensus model. We summarize these methods in the following.

Amalgamation involves combining models through model parameters granularity operations, such as median [12, 175] and coordinate-wise averaging with consideration of heterogeneity [129, 156], security [206], scalability [183], matching [219, 243], specificity [71], generalizability [177], resulting in a combination with weak separation. This reusing approach is widely used in FL works and is often referred to as "aggregation" procedures for local models. Here, we avoid using the term "aggregation" to distinguish it from "combination". The latter is often used interchangeably with "combination" in software licenses (e.g. Artistic, GPL).

FedAvg [156] is the most popular model averaging method in FL with many follow-up works. For instance, Sun *et al.* [206] proposed applying norm thresholding of local model updates to defend against backdoor attacks. Similarly, Blanchard *et al.* [12] proposed using more robust median-based amalgamation for resilience against Byzantine behavior. Consider the ordering of parameters, Wang *et al.* [219] match and average the NNs parameters layer-wise across clients, based on their similarities. Yu *et al.* [243] further attribute the misalignment in FL models to the non-IID training data, propose allocating an independent structure for each class and updating models through a feature paired averaging strategy. **Even though** amalgamation mechanisms can achieve a balance between model performance and resource efficiency by maintaining only one global model, they often rely on multiple rounds of communication to converge, which is not applicable in a query-based FL scenario. So, instead of trying to directly concatenate multiple sources of models while dealing with intricate parameter mismatch, transferring the latent knowledge learned by local models to a new model is a good alternative (i.e. Federated Distillation [91, 99]).

Another direction of model amalgamation is leveraging Bayesian nonparametrics to learn the shared global latent structures among local models [112, 246, 247]. These methods, known as Model Fusion, can identify distributions of neural components across local models and only fuse the components with the same distribution, which can be regarded as a model compression between FedAvg (coordinate-wise averaging) and combination (w/o averaging). However, the model fusion strategies rely on multiple communication rounds to boost the fusion efficiency, and the model performance of one-shot fusion is even worse than that of Ensemble. Most recently, Su *et al.* [201], inspired by null-space in continual learning [109, 224], propose MA-Echo which leverages layer-wise projection matrices to preserve the original loss of local models after amalgamation. Their evaluation results present a moderate improvement in one-shot setting compared to FedAvg and ensemble. **Unfortunately**, this improvement is not consistently observed in multiple-round experiments. Meanwhile, to tackle the issue of catastrophic forgetting, FedPR [53] follows similar ideas to facilitate the server's learning of visual prompts from clients for MRI reconstruction applications, **but** the improvement compared to FedAvg is limited even in multi-round setting.

It is worth noting that our taxonomy is based on the form of the resulting model, which may not be entirely consistent with the terminology used in the technical perspective. For example, Bayes Model Averaging (BMA) [35] estimates posterior probabilities of each model given the observed data, which results in a separable weighted model. Therefore, it should be classified as Combination instead of Amalgamation like FedAvg. This novel taxonomy method is useful for analyzing compatibility with licenses. For instance, coordinate-wise operations and fusion of model parameters generate fine-grained combinations of models that are almost irreversible, which corresponds to clauses such as adapt, modify, dynamic link, etc., in software licenses.

Table 4. Summary of privacy-preserving **Distillation** works in the field of FL. Some works are listed multiple times because they contain multiple KD procedures with different strategies. Works with naming conflicts are distinguished by subscript.

Strategies		FL Studies
KD@Server	w/ Validation Set	FedED [202]
	w/ Unlabeled Data	FedDF [139], One-shot FL [72], FedBE [28], PerAda [232], FedET [34]
KD@Client w/ Local Data	from Global Model	FedFusion [239], FedKD ₂ [230], MOON [125], FedNTD [115], FedMLB [105], FedCAD [80], FedAlign ₁ [157], FedAlign ₂ [255]
	from Other Clients' Model	FedMatch [92]
	from Self Model	FedFusion [239], FedDistill [97], FedKD ₂ [230], MOON [125], FCCL [86], pFedSD [100], RSCFed [136]
KD w/ Public Unlabeled Datasets		FedKT [124], FedMD [117], FedAD [66], FedMD-NFDP [203], FCCL [86], FedAUX [191], RHFL [52], FedKD ₁ [67], Cronus [24], KT-pFL [254], DS-FL [88]
KD w/ Generated Data (DFKD)		DENSE [252], FedCAVE-KD [82], FedGen [268], FedFTG [258]
KD w/ Differential Privacy		FedKC [220], FedSSL [49]

Distillation was initially proposed by Hinton *et al.* [84] to transfer knowledge from a batch of independently trained neural network models (Specialists) to create a new Generalist model. Their motivation was to explore the parallelization of training of specialists and improve the efficiency of distributed NNs modeling[40]. Each specialist only learns fine-grained distinctions of a subset of classes, which is very similar to the non-IID setting in FL [123]. Besides, by using Knowledge Distillation (KD), we can compress wide and deep teacher networks into lightweight student networks [189], which is promising for addressing system heterogeneity in cross-device FL [138]. Therefore, it is natural to extend the KD technologies to FL filed [28, 66, 97, 117, 124, 139, 203, 230]. Actually, many recent FL works [24, 52, 66, 67, 78, 86, 88, 117, 148, 202, 203, 254] solely leverage KD without following the model averaging paradigm of FedAvg, we leave this discussion for later.

Despite directly retraining a Generalist model through knowledge distillation (KD), an alternative approach is to construct an ensemble of knowledge. For example, Furlanello *et al.* [55] consecutively generate student models with the guidance of knowledge distilled from earlier generations and find that the ensemble of multiple generations of internal models achieves state-of-the-art performance. Dvornik *et al.* [46] leverage the distilled knowledge from each learner to encourage cooperation and prediction diversity within the population, which leads to better ensemble results. In the context of FL, the main **advantage** of distillation is the decoupling between knowledge distillation and knowledge learning. This allows us to split the model architecture for the purpose of system heterogeneity and efficiency [212, 216]. Moreover, the well-learned knowledge from clients only needs to be communicated once [66, 67], while the server can perform multiple epochs of local training to complete the transfer. The **drawback** of KD is that it is data-dependent and the shared knowledge may be extracted from local sensitive data, which exposes a new attack surface for potential model inversion attacks [54, 106]. To mitigate this issue, some efforts [49, 220] have been made to add differential privacy noise [47] to the shared content.

In general, there are three mechanisms for avoiding the sharing of sensitive knowledge. First, push the KD procedure to the server-side, where the knowledge of local models is transferred to the global model through a validation set [202] or unlabeled dataset [28, 34, 72, 139, 232] held by the server. Second, we can keep the KD procedure at the client-side, allowing the knowledge of the global model [80, 105, 115, 125, 157, 230, 239, 255], other clients' models [92] or self-model [86, 97, 100, 125, 136, 230, 239] to be transferred based on the local training data. In the above two strategies, only model parameters are exchanged in the training network, which means they can provide the same level of privacy protection as traditional FL.

The last mechanism is to assume that a public unlabeled dataset, which does not contain sensitive information, can be accessed by both the server and clients for KD [24, 52, 66, 67, 86, 88, 117, 124, 191, 203, 254]. Sharing these extracted contents will not raise any privacy concerns, and only minimal communication is generated during KD

Table 5. Classification of **Generation** works in the field of FL. Some of the works are also listed in Table 4 because they utilize hybrid model reuse mechanisms.

	Enriching Training Set	Improving Generalization	Enabling Semi-supervised Learning
For Training	FedSage+ [256], GFL [33], FRD [21]	Fed-ZDA [76], FOSTER [245], FedDG [141], DynaFed [174], SDA-FL [134], FedMix [241], FedCAVE-Ens [82]	FedDISC [235], SemiFL [42]
For KD	DENSE [252], FedBE [28], FedDyn [99], FedZKT [259]	FedGen [268], FedFTG [258], FD+FAug [91], FedCAVE-KD [82]	FedSSL [49]

for the purpose of aligning sample IDs. In cases where such public datasets are not available on the server, a recent approach called Data-Free Knowledge Distillation (DFKD) has been proposed by Lopes *et al.* [145]. This approach regenerates batches of data based on layer activation statistics or spectrum coefficients collected during training phase, and this synthetic data is then used for distillation. DENSE [252] is the first attempt to extend DFKD to FL. It leverages the ensemble of local models to guide the training of a data generator on the server, and the generated data is then used to distill the knowledge from local models to the global model. FedCAVE-KD [82] leverages locally trained conditional autoencoders (CVAEs) [107] to generate samples based on the data distribution of clients. These CVAEs are sent to server used to construct a global generator via KD, which will later provide synthetic training data for the global discriminator.

It is worth noting that in the query-based FL setting, direct access to the original data is not available, so the second mechanism cannot be applied directly. A circumvention method is to train a generator following the inspiration of DFKD. Fortunately, this is practicable if the workflow and history information of modeling are tracked and queryable, as we advocated in Section 4.2.2. Recalling that, as shown in Fig. 4(b), Generation is the last category in our taxonomy. Actually, such a hybrid model reuse strategy is quite common in FL. For example, the previously mentioned DENSE [252] incorporates three model reuse mechanisms: Combination (creating an ensemble), Generation (generating synthetic data), and Distillation. Therefore, our taxonomy can cover traditional FL works, such as FedAvg and MOON [125], as well as the broad sense FL, including Federated Distillation [91, 99] and Ensemble Learning [198, 223]. We provide a comparison of these hybrid works in Section 4.3.5. The summarize of above privacy-perserving KD works is given in Table. 4.

Generation is designed to generate synthetic samples that resemble the original data distribution by building a probabilistic model [61] or deep learning model [20, 68, 107] that can capture the underlying distribution pattern and latent structure of original data. Generally speaking, generation techniques can be classified into three categories: data-level, probabilistic, and representation-based approaches. Data-level approaches involve sample granularity operations such as interpolation [26, 251] and augmentation [229] to generate synthetic features based on the original feature space of data. Even though these methods are training-free and easy to implement, they cannot be directly applied to the FL setting due to privacy concerns. Recent proposed FedMix [241] aims to alleviate the negative effect of non-IID data by using *mixup* [251], where the average of local data is linearly interpolated with the training data to generate augmented samples. However, the potential risk of data leakage when sharing the mixup data is not comprehensively evaluated in the original work.

Probabilistic approaches aim to estimate the real data distribution using probabilistic method. For example, Markov Chain Monte Carlo (MCMC) [61] methods construct a Markov Chain that converges to the desired target distribution by iteratively proposing new states based on the current state of the chain and acceptance probabilities. Gaussian Mixture Models (GMM) assumes the data is generated from a mixture of Gaussian distributions and can generate new samples by sampling from the learned distributions. Representation-based approaches try to reconstruct the data from latent feature space. For instance, Variational Autoencoders (VAEs) [107] learn the distribution of the latent representation space given the observed data and then use a decoder network to

reconstruct data based on sampled latent representations. Generative Adversarial Networks (GANs) [68] train a generator network to produce samples that resemble realistic data by optimizing an adversarial objective against a discriminator network.

Compare to the other model reuse mechanisms, generation has three unique **advantages**. The first advantage is visualization and verification. Unlike the extracted knowledge in distillation, the quality of generated content can be visualized and validated by humans. This capability aids in assessing the contributions made by participants in terms of generating valuable content. Second, the flexibility of generation methods allow us to generate data with any desired amount or class, which enables more effective handling of imbalanced [26] and non-IID [258] data. The third advantage is multi-format sharing. Participants have the freedom to choose the form of their contributions. For example, they can upload the learned generative models in source code (e.g., Stable Diffusion [188], GPT-2 [178]) or binary form, upload synthetic data, or provide model inference APIs like ChatGPT. This sharing policy greatly empowers the model community in an open FL platform, fostering collaboration and knowledge sharing.

Given the aforementioned advantages, generation methods have been extensively studied in the field of FL. As summarized in Table. 5, these works can be classified into two main categories: generation for training [21, 33, 42, 76, 82, 134, 141, 174, 235, 245, 256], generation for KD [28, 49, 82, 91, 99, 252, 258, 259, 268], and serving three purposes: enriching the training set [21, 28, 33, 99, 252, 256, 259], improving generalization ability [76, 82, 91, 134, 141, 174, 245, 258, 268], and enabling semi-supervised learning [42, 49, 235]. As an example of generation for training, FedSage+ [256] trains a missing neighbors generator to mend the links between cross-subgraph nodes, thereby increasing the connectivity of local data and benefiting from this collaboration across clients. Previous mentioned FedCAVE-KD [82] is an example of generation for KD, where locally trained CVAEs and local label distributions are uploaded to the server for DFKD, ensuring privacy while also enhancing generalization of global model. Another example is FedGen [268], where the generator is maintained by the server and sent to clients in each round. The generator has knowledge about the global view of the data distribution, which is used to KD into the local models, thereby enhancing their generalizability. The last application of generation is in semi-supervised learning, which is a common real-world scenario where the client data is unlabeled. For example, FedDISC [235] leverages the average and cluster centroids of hidden representations across pseudo-labels as input to a pre-trained diffusion model, aiming to generate high-quality samples for training.

In fact, the three purposes of generation correspond to three types of data heterogeneity in FL [123]: Quantity Skew, Label Distribution Skew (non-IID), and Missing Labels, which are challenging to address with traditional model amalgamation methods. Therefore, the hybrid model reusing strategies, which leverage each other's strengths, have become a common paradigm in recent FL studies [33, 82, 99, 232, 235, 245, 255]. Therefore, in the next section, we will summarize the popular hybrid model reusing studies in FL and then filter the studies that are suitable for a sustainable open FL platform.

4.3.5 Hybrid Model Reusing in FL. Following the taxonomy we introduced in Section 4.3.4, it can be observed that almost all FL studies can be regarded as a permutation of four model reuse mechanisms: Combination, Amalgamation, Distillation, and Generation. To enhance our understanding of current model reusing studies and identify methods applicable for constructing an open FL platform, we provide a comprehensive summary in Table 6. We employ different colors and fonts in Table 6 to emphasize the distinctions among studies, while certain processes have been omitted without ambiguity. In addition, we have listed the main goals of each study, and only those with explicit designs, experiments, or proof are counted. Please refer to the table caption for the explanation of our denotations. As an example, the process of RSCFed [136] involves the following steps: ① KD, the knowledge is extracted as the softmax values from the self model based on local private data (ref. Table. 4) and performed at the client-side; ② Model exponential moving averaging performed at the client-side; ③ Simple Model Averaging performed two times at the server-side. This entire process is repeated across multiple communication

Table 6. Comparative analysis of FL studies categorized by our taxonomy for batch model reuse mechanisms. Studies **applicable** and **conditional applicable** to query-based FL are marked with different colors; **Purple** denotes operations completed on **Server**, or knowledge distilled from **Global or Consensus Model**; **Blue** denotes operations completed on **Clients**, or knowledge distilled from **Local, Personalized, or Generative Models**; **Knowledge or Generated Content** based on **Public, Proxy or Generated** data, and **Knowledge or Generated Content** based on **Local, Private or Sensitive** data; []*1: one round of communication (aka one-shot), []*N: multiple rounds of communication, processes ahead ...[] are performed only once (i.e. preprocessing), processes inside [...] are main functional part; Slash "/": model training based on *private* data, Comma ",": model training based on **non-sensitive** data; Goals of works: Efficiency Heterogeneity Privacy.

FL Studies	Combination	Amalgamation	Distillation	Generation	Process	Goals
FedAvg [156]		Model Avg			[/A]*N	EH
FedAD [66]			KD Attention, Logits		[/D]*1	HP
FedKD ₁ [67]			KD Weighted Logits		[/D]*1	EHP
FedED [202]			KD Logits Avg on Global Validation Data		[.D]*N	EHP
FedIris [148]			KD Hidden		[D]*N	H
FedMD [117]			KD Logits Avg		[D]*N	H
FedMD-NFDP [203]			KD Logits/Softmax/Argmax Avg		[/D]*N	HP
DS-FL [88]			KD Entropy Reduced Logits Avg		[/D]*N	EH
RHFL [52]			KD Weighted Logits		[/D]*N	EH
KT-pFL [254]			KD Learned Weighted Softmax		[/D]*N	EH
Cronus [24]			KD Robust Mean Estimation of Softmax		[/D]*N	EHP
FedDISC [235]				Synthetic Data	[G]*1,	EH
FRD [21]				Mixup Data	[G]*1,	E
One-Shot FL [72]	Output Avg		KD Softmax		[/CD]*1	EP
FedDF [139]		Model Avg	KD Logits Avg		[/AD]*N	HP
PerAda [232]		Adapter Avg	KD Logits Avg		[/AD]*N	EHP
FedFiMa [27]		Rep. Layer Avg	KD Hidden Avg		[/AD]*N	EH
FedFusion [239]		Model Avg	KD Hidden, Hidden		[DA]*N	E
FedNTD [115]		Model Avg	KD Not-True Classes Softmax		[DA]*N	H
FedKC [220]		Model Avg	KD Clustered Hidden Avg		[DA]*N	HP
FedDistill [97]		Model Avg	KD Softmax of Latest Local Model		[/DA]*N	H
pFedSD [100]		Model Avg	KD Softmax of Previous Local Model		[/DA]*N	H
FedMLB [105]		Model Avg	KD Softmax, Scaled Softmax		[/DA]*N	EH
FedAlign ₁ [157]		Model Avg	KD Lipschitz Constants [196]		[/DA]*N	EH
MOON [125]		Model Avg	Contrastive Learning Hidden, Hidden		[/DA]*N	EH
FedCAD [80]		Model Avg	KD Class-Wise Softmax		[/DA]*N	H
FedGKT [78]			KD Logits KD Logits, Hidden, Argmax		[/D/D]*N	EH
FCCL [86]			Contrastive Learning Logits Avg Continual Learning Logits		[/D/D]*N	H
GFL [33]		Model Avg		Synthetic Data	[/G[A]]*N	HP
FOSTER [245]		Model Avg		Synthetic Outliers	[/G[A]]*N	EH
FedDG [141]		Model Avg		Interpolated Data	[/G[A]]*N	H
SemiFL [42]		Model Avg		Augmented and Mixup Data	[/G[A]]*N	H
NeighGen [256]		Gradient Avg		Synthetic Node	[/G[A]]*N	H
FedSage [256]		Model Avg			[/A]*N	
Fed-ZDAC [76]		Model Avg		Zero-shot Synthetic Data	[/G[A]]*N	HP
Fed-ZDAS [76]		Model Avg		Zero-shot Synthetic Data	[/G[A]]*N	
FedMix [241]		Model Avg		Mixup Data Mixup Data	[/GA]*NG,	HP
FedDyn [99]			KD Hidden, Logits Avg	Synthetic Data	[/GD]*N	E
FD+FAug [91]			KD Per-Class Logits Avg	Synthetic Data	[/G/D]*N	EP
FedCAVE-Ens [82]	Collection		KD Softmax	Synthetic Data	[/C[G]]*1	H
FedCAVE-KD [82]					[/C[GDG]]*1	H
Fed-ET [34]		Rep. Layer Avg	KD Argmax, Weighted Logits		[/ADA]*N	EH
FedBE [28]		Model Avg	KD Softmax Avg	Synthetic Model	[/AGD]*1	H
DynaFed [174]		Model Avg		Synthetic Data	[/A]*NG[A]*N	EH
FedAUX [191]		Model Avg	Contrastive Learning Hidden, Hidden KD Weighted Logits		[.D[A/D]]*N [.D[A/D]]*1	HP
FedKD ₂ [230]		Gradient Avg	KD Hidden, Attention, Logits KD Hidden, Attention, Logits		[/DAD]*N	EH
FedGen [268]		Model Avg	KD Softmax KD Logits Avg	Augmented Data	[D[/G,AD]]*N	EHP
SDA-FL [134]		Model Avg	KD Argmax	Synthetic Data Augmented Data	[/C[G,AD]]*N	HP
FedKT [124]	Voting Voting		KD Argmax KD Argmax		[/CDGD]*1	HP
FedMatch [92]	Voting	Model Avg	KD Argmax		[/C/DAA]*N [.CDA]*N	EH
FedFTG [258]		Model Avg	KD Softmax, Softmax KD Softmax	Synthetic Data	[/AGDD]*N	EH
RSCFed [136] (Unlabeled Case)		Model EMA Model Avg	KD Softmax		[/DAAA]*N	H
FedAlign ₂ [255]		Model Avg	Contrastive Learning Argmax, Argmin		[/DDAA]*N	EH
FedSSL [49]			KD Softmax KD Softmax, Interpolated Softmax	Synthetic Data	[/GD/GD]*N	HP
DENSE [252]	Collection		KD Logits Avg, Batch-Wise Statistics, Softmax KD Softmax, Softmax	Synthetic Data	[/C[G,DGD]]*1	HP
FedZKT [259]			KD Softmax, Softmax Avg KD Softmax Avg KD Softmax	Synthetic Data	[/GDGDGD]*N	H

rounds until completion. In this way, we can categorize these works and make intuitive comparisons between them.

Finding 1. Amalgamation and Distillation ([AD] or [DA]) are the most popular combo in FL studies, followed by Distillation as a standalone ([D]) strategy and Generation before Amalgamation ([GA]).

Due to the presence of parameter mismatch [219, 243, 246], using solely amalgamation often lead to weight divergence [132, 208], particularly in scenarios with high data skew. As a result, distillation, which provides a global view of the data distribution, serves as a complementary solution for addressing data heterogeneity (indicated as "H" in Table 6). However, to achieve acceptable performance, amalgamation requires multiple accesses to local data for training and multiple communications for model averaging ([AD]*N or [DA]*N), which makes it challenging to apply in one-shot FL settings.

On the other hand, we can fuse the distilled knowledge for training without any model amalgamation ([D]*N or [D]*1). However, additional precautions should be taken to prevent sensitive data leakage. One common approach is to introduce an auxiliary public unlabeled dataset for knowledge extraction (except for FedED [202], which uses labeled validation set, ref. Table 4). Getting rid of the limitation of amalgamation, these distillation studies (i.e., FedAD [66], FedKD₁ [67]) enable the feasibility of one-shot learning, making them good candidates for constructing a query-based FL platform. Meanwhile, the generation approaches also offer the same one-shot capacity (i.e., FedDISC [235] and FRD [21]) as distillation by directly generating synthetic data for fusion. This one-shot capacity can also be extended to the hybrid case, such as FedCAV [82], FedBE [28], FedAUX [191], DENSE [252]. That is why the final step in all one-shot solutions is typically distillation or generation on the server-side (excluding local training), rather than amalgamation. But it is worth noting that one-shot feasibility is not sufficient and necessary in the context of query-based FL. For example, in FRD [21], participants generate mixup data for server training rather than contributing their models. Currently, it is evident that the once strong connection between model averaging and FL has become blurred, and distillation has emerged as a popular method in the field of FL.

Finding 2. Combination is the least common model reusing method in FL studies.

One drawback of using combination in the FL context is the high communication consumption required for broadcasting the combined model to multiple participants, which can be expensive in terms of bandwidth and latency. Hence, a practical approach is to compress the contributed models through methods like amalgamation or distillation, which may already implicitly include combination. However, to avoid redundancy, we did not include these temporary combinations in our table.

Finding 3. Amalgamation after Distillation ([DA]) primarily distills knowledge from private data, while Distillation after Amalgamation ([AD]) and solely Distillation ([D]) primarily distill knowledge from non-sensitive data.

This difference arises from two different FL agreement mechanisms. One strategy is to leverage model amalgamation to achieve agreement ([DA]). For example, the knowledge from multiple data sources is generalized by applying appropriate weighting before being transferred to local models, which are then averaged to achieve the target model. Another strategy is to leverage a public dataset to achieve agreement ([D] or [AD]). In this approach, the knowledge distilled from multiple local models can be fused to a consensus agreement and then applied to the target model, eliminating the need for model amalgamation.

Question: How to select the suitable model reusing method for query-based FL?

From the previous discussion, we have demonstrated how to summarize recent FL studies from a model reusing perspective. Similarly, to select a suitable method for query-based FL, we can refer to Table 6 and consider the following factors:

- **Data Dependency.** Recalling that query-based FL is contactless (Section 4.1), which means we cannot access the training data again once the model has been uploaded by the entity. Therefore, any method that requires multiple communication rounds of local or sensitive data access is not applicable to query-based

FL. Such as, local data dependency due to local training (FedMD [117], DynaFed [174], etc.), distillation (FedFusion [239], MOON [125], etc.), generation (SemiFL [42], NeighGen [256], etc.). So, refer to Table 6, the filtering criteria for unqualified methods can be expressed as [.../...]*N, [...D...]*N with *knowledge in italic* and [...G...]*N with *generated content in italic*.

- **User Privacy.** Due to the openness of the system, directly sharing embeddings from a pre-trained encoder or mixup of local data poses a risk of leakage (FedDISC [235], FRD [21]). It is strongly discouraged to include such methods, even if they have one-shot feasibility.
- **Compatibility.** Additional, since query-based FL is model agnostic, it is not always possible to guarantee the compatibility of coordinate-wise operations required by model amalgamation. Therefore, the applicability of methods that involve model amalgamation may be limited in this context. We call these methods are conditional applicable to query-based FL.

In summary, we have marked the applicable and conditionally applicable methods to query-based FL in Table 6 in red and orange, respectively. Even though the KD procedure of DENSE [252] relies on batch-wise statistics collected during local training, we consider this information to be non-sensitive. Therefore, we include it in the applicable methods. Please note that some single combination or amalgamation approaches, such as Fed-ensemble [198] (only combination) and Models Fusion [112, 246, 247] (only amalgamation), can be directly applied in a query-based FL setting. However, to avoid redundancy, these studies have been omitted from Table 6. By now, we have witnessed the success of using the new taxonomy, and in the next section, we will discuss how to combine our taxonomy with the context of model licenses.

4.3.6 Model Reusing vs. Model Licenses. We have demonstrated that almost all FL studies can be regarded as a permutation of model reusing methods. Therefore, we can further analyze the corresponding clauses in model licenses perspective for FL studies by decomposing them into model reuse methods. Recalling that there are four kinds of model reusing mechanisms: Combination, Amalgamation, Distillation, and Generation, which result in four forms of outputs: Combination with strong separation, Combination with weak separation, Derivative from learned concepts, and Derivative from learned distributions. By interpreting "work" as "model" rather than as "software", we can easily identify the applicable clauses for different model reusing mechanisms.

We present the analysis of model licenses for model reuse in Table 8. The analysis covers the most popular model licenses (adopted by over 100 released models) on Hugging Face, which include free software licenses, free content licenses, and AI model licenses. For simplicity, we have merged some similar licenses without loss of clarity. To avoid license conflicts when engaging in batch model reuse, it is preferable for the reused model to be considered an **independent** work or fall under an **undefined** category, not covered by the original license. Additionally, we can refer to Table 8 and consider the following factors:

- **Differences in terminology.** In the definitions of licenses, connecting multiple works into a separable union is typically referred to as *aggregation*, *redistribution*, and *reproduce*, which is completely different from the concept of *model aggregation* in the FL context. Therefore, it is necessary to refer to Table 8 for the corresponding delineations of each model reuse mechanism instead of relying solely on the technical name.
- **Restrictions of combination and amalgamation.** As shown in Table 8, the majority of model licenses have specific terms and definitions regarding these two methods, except for blackbox combination. This implies that there may be potential restrictions that need to be taken into account and complied with. These restrictions may also proliferate to the reused results if original licenses of models are copyleft, such as GPL-3.0, CC-BY-SA, CC-BY-NC-SA, etc. Therefore, we recommend avoiding the use of models and datasets under such copyleft licenses (ref. Fig. 4(b) and Tabel 3) for batch model combination and amalgamation.
- **User behavioral restrictions of responsible AI licenses.** OpenRAIL licenses [36] clearly define all four model reuse mechanisms, which means the effect of copyleft-style behavioral-use clauses will spread to the reused results, which can potentially result in the licensed artifacts becoming closed source [70] (ref.

Table 8. Analysis of the model licensing clauses corresponding to different batch model reuse mechanisms, denoted by "keywords in licenses" -> "delineation of reused results", ✗: undefined. Note: GPL-3.0, CC-BY-SA, CC-BY-NC-SA are copyleft.

	Combination	Amalgamation	Distillation	Generation
	Combinated Work with Strong Separation	Combinated Work with Weak Separation	Derivative Work from Concepts	Derivative Work from Distributions
Apache-2.0	Separable -> Independent Work	Modify -> Derivative	✗	✗
MIT	✗	✗	✗	✗
AFL-3.0	✗	Modify -> Derivative	✗	✗
GPL-3.0	Blackbox: Aggregate -> Independent Work Other: Link -> Modified Version	Modify -> Covered Work	Output no constitutes a covered work -> Independent Work	Output no constitutes a covered work -> Independent Work
Artistic-2.0	Blackbox: MereAggregation -> Independent Work Other: Link -> Modified Version	Aggregate -> Modified Version	✗	✗
BSD-3-Clause	Blackbox: Redsitribution in binary forms -> ✗ Other: Redistribution of source code -> ✗	✗	✗	✗
WTFPL-2.0	✗	✗	✗	✗
OpenRAIL Licenses	Transfer of patterns of output -> Derivative	Transfer of patterns of weights -> Derivative	Transfer of patterns of activations -> Derivative	Transfer of patterns of output -> Derivative
Creative Commons Licenses	Reproduce -> Adapted Material	Adapt -> Adapted Material	✗	✗
CC0-1.0	Reproduce -> Independent Work	Adapt -> Independent Work	✗	✗

Section 4.3.2). To prevent license proliferation [65], it is not recommended to reuse models under these OpenRAIL licenses.

Lastly, we can further analyze the potential license conflicts in hybrid model reuse methods. Let's consider the example of DENSE [252], where the process is $/C[G,DGD]*1$ and assume that the local models are licensed under GPL-3.0. In this case, the collection of local models should be treated as a whitebox in order to distill the logits value from it. As a result, this collection should be considered a *modified version* of the original works according to the terms of GPL-3.0. However, the generation and distillation processes of DENSE are based on non-sensitive data and result in the creation of an independent work. Considering that GPL-3.0 is a copyleft license, the reused results should be licensed under GPL-3.0 if the release includes the collection in its whitebox form. Otherwise, the reused results can be considered an independent work without any specific license restrictions.

The example above demonstrates that analyzing hybrid methods under a copyleft license can be complicated. Therefore, selecting models, algorithms, datasets with more permissive licenses, as advocated in Section 4.3.2, can make things easier and facilitate the model reusability of open FL platforms.

4.4 How to Protect Models

In the previous sections, we have extensively discussed the construction of a query-based FL platform from both technical and legal perspectives. Nonetheless, the matter of model management and protection continues to be a significant concern, raising questions such as *How can I protect my models from plagiarism after they are released?* In general, there are three kinds of mechanisms that can be employed to protect DNN models: authorization [75], watermarking [210], and fingerprinting [116]. Authorization mechanisms, including hardware-based memory encryption techniques like TEE, can effectively prevent unauthorized access to the model copy. Additionally, researchers have explored embedding authorization mechanisms within the DNN architecture itself, such as with

passport layers [50, 253]. However, the need for specific hardware and modifications to model architectures can significantly increase the barriers for participants and compromise the openness of query-based FL platforms.

As passive protection methods, watermarking and fingerprinting can detect potential infringement while preserving the openness of the model. A watermark can be embedded into DNNs through training or fine-tuning with a modified loss function [214] or trigger data [37] acting as a backdoor [10]. On the other hand, fingerprinting strategies aim to generate an identifier for each model based on snapshots of training history [95] or inference results that approximate decision boundaries [29]. Note that the technical details of IP protection methods are beyond the scope of this survey. We recommend referring to up-to-date surveys such as [168, 205]. Additionally, it is important to recognize that the goal of query-based FL platforms is not to provide perfect protection against model plagiarism and unauthorized use. Interestingly, certain model reusing strategies like KD and ensemble methods are even regarded as model extraction attacks within the realm of DNN protection [25]. This highlights the inherent contradiction between promoting model reusing and preventing all forms of model plagiarism. As a result, it is necessary to determine the scope of protection and strike a balance between model protection and platform openness.

First, it is helpful to consider the following requirements for model protection in the context of query-based FL:

- **Non-invasive.** Any attempt to invasively embed backdoors into the weights and architectures of models is likely to result in changes to their functionalities and could lead to unexpected failures after deployment. Meanwhile, these backdoors can be exploited by attackers to manipulate the model's predictions [133]. Accordingly, it is more recommend leaving the decision of adding invasive protection to the users instead of forcing it through platforms.
- **Compatible.** Due to the model agnostic nature of query-based FL, relying on protection mechanisms that are specific to certain model structures and formats will limit the applicability of the platform. For instance, the passport layer [253] is built upon the normalization layer and requires joint training with the target model for ownership verification. However, in practice, both the normalization layer and whitebox access to the model may be unavailable. Therefore, considering the compatibility of model protection mechanisms is essential to ensure wide support for model sharing in query-based FL.
- **Permissive.** As mentioned earlier, it is not essential to identify and address every instance of plagiarism in query-based FL. On the contrary, we encourage platform users to engage in model mining and reusing, as outlined in Section 4.3.4. Therefore, model protection methods should be permissive enough to allow for model reusing while still identifying the less creative effort operations that result in minimal or no change to the model's functionality, such as naive replication, quantization, pruning, and invariant neural swapping. Note that the presence of sufficient human creative effort is an important criterion for determining the copyrightability of a computer-generated work [163]. The consideration of copyrightability can serve as a guiding principle in determining the scope of model protection in query-based FL.
- **Large-scale cost-effective.** Unlike traditional FL, where the size of training networks in each round is fixed, the size of a query-based FL platform is continuously expandable. Therefore, it is undesirable if the potential conflicts [116], required bit-length, and deployment cost [37, 214] of model protection solutions such as watermarking and fingerprinting increase with the platform size. This suggests that solutions that require modifying optimization goals and training or fine-tuning with trigger data to embed identity information into the target model should be excluded.

Recently, several model protection algorithms have been proposed to address the challenge of model protection in FL. Tekgul *et al.* [210] propose WAFFLE that uses augmented Gaussian noisy images as a watermark set to determine the ownership of the global model. However, this method is invasive and incurs high costs due to multiple rounds of training. To ensure reliable watermarking for FL participants, FedIPR [116] embeds different watermarks into models of different participants through training with additional trigger samples and a modified

optimization goal. This method is designed for model verification on the client-side, so it is independent to the model management in FL platforms. FedTracker [197] embeds personalized local fingerprints into the Batch Normalization (BN) layer to enable traceability of model leakers. One limitation of FedTracker is that its fingerprinting strategies are not compatible with other DNNs that do not use BN and do not provide whitebox access. These examples highlight the incompatibility between the IP protection methods designed for traditional FL and the requirements of the query-based FL scenario, which have different protection goals and targets.

Based on the above observation and the taxonomy of deep IP protection [168, 205], dynamic fingerprinting strategies with blackbox verification support are considered suitable model protection methods for query-based FL. These methods aim to approximate the similarities between the decision boundaries of different models by evaluating the value of a well-tailored testing metric on a self-constructed testing set. A typical example is DeepJudge [29], which employs an ensemble of multi-level (Property, Neuron, Layer) testing metrics to achieve confident and robust plagiarism identification. The verification process of DeepJudge can be evaluated in a blackbox setting by calculating distances based on model predictions. However, the generation of testing set in DeepJudge requires whitebox access to the suspect models in order to calculate adversarial samples, which may be unreachable if the suspect models are in binary format.

Another example is Zest [94], which randomly samples several training images and then applies super-pixel and segmentation techniques to construct the testing set. However, this testing samples generation method is limited to images and may expose private training data. A compromise approach is to seek non-sensitive or desensitized testing set from users when they upload their models. Inspired by DeepJudge, we can develop an ensemble of multi-level testing strategies for query-based FL. In the first step, we can compare the hash codes (e.g. MD5, SHA-256) of the raw model weights or its binary execution to rapidly filter out cases of naive replication plagiarism. Then, in the second step, we can filter out cases of quantization or invariant neural swapping plagiarism by comparing the distance in predictions obtained from an out-of-distribution dataset. Finally, we can further evaluate the similarities between models using testing-based approaches such as DeepJudge and Zest, which can detect cases of pruning and direct KD plagiarism. Furthermore, if the workflow information is supports it, we can swiftly eliminate batch model reusing from being suspected of plagiarism.

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