Model-Centric Federated Machine Learning

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Tranditional Federated Machine Learning follows a server-domincated cooperation paradigm which narrows the application scenarios of federated learning and decreases the enthusiasm of data holders to participate.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Additional Key Words and Phrases: datasets, neural networks, gaze detection, text tagging

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1 INTRODUCTION

Introduction: Federated Learning [14].

Four roles in FL systems design: the data owners, the model users, the coordinators, the auditors.

1.1 Related Surveys

In recent years, 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 appllications 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 summaried by Yang *et al.* [29]. They categorize 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 [24, 28]. Following this, an increasing number of surveys have emerged focusing on enhancing FL system design [4, 11, 13, 14, 31]. From the algorithmic perspective, personlized FL [12, 25] aims to learn personlized models for each client to address the challenge of statistical heterogeneity [18]. Besides, the privacy-perserving computing platforms and model aggregation protocols for FL systems also been widely studied and sumaried by [8, 16, 17, 30]. Furthermore, many advanced FL architectures had been proposed, such as asynchronous [26], decentralized and blockchain-based FL frameworks [19, 21, 34]. 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 geogrphically distributed medical insitutions can enhace medication recommendation, drug-drug interaction prediction and medical image analysis in a collaborative manner without exchanging any sensitive data [5, 20, 23, 27]. The massive real-time data generated by IoT devices in smart cities [22, 32], industries [6], vehicles [7] 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 [2, 3, 9].

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

		Challenges					Contents		
Scenarios/Tasks	FL Surveys	Efficiency	Heterogeneity	Privacy	Incentive	Decentralized	SYS	APP	SDC
General	Yang *et al.* [29]	✓	✓	✓	✓	✓	✓	✓	✓
	Li *et al.* 2020 [14]	✓	✓	✓		✓	✓	✓	✓
	Zhang 2021*et al.* [31]	✓	✓	✓			✓	✓	✓
	Gupta *et al.* [10]	✓	✓	✓		✓	✓	✓	✓
	Xu *et al.* [26]	✓	✓	✓		✓	✓	✓	✓
	Li *et al.* 2021 [13]	✓	✓	✓	✓	✓	✓	✓	✓
	El *et al.* [8]			✓		✓	✓		✓
	Kulkarni *et al.* [12]	✓	✓				✓		✓
	Liu *et al.*[16]	✓		✓		✓	✓		✓
	Tan *et al.* [25]		✓				✓		✓
	Zhu *et al.* 2021 [33]		✓				✓		✓
	Ma *et al.* [18]	✓	✓	✓			✓		✓
	Aledhari *et al.* [4]	✓	✓				✓	✓	✓
	Kairouz *et al.* [11]	✓	✓	✓	✓	✓	✓	✓	✓
	AbdulRahman *et al.* [1]	✓	✓	✓	✓		✓	✓	✓
	Lim *et al.* [15]	✓	✓	✓	✓		✓	✓	✓
Healthcare	Xu *et al.* [27]	✓	✓	✓			✓	✓	✓
	Pfitzner *et al.*[20]	✓	✓	✓			✓	✓	✓
	Antunes *et al.* [5]		✓	✓				✓	✓
	Rieke *et al.* [23]		✓	✓		✓	✓	✓	✓
IoT	Zhang 2022*et al.* [32]	✓	✓				✓	✓	✓
	Boopalan *et al.* [6]	✓	✓	✓	✓	✓	✓	✓	✓
	Ramu *et al.* [22]	✓	✓	✓		✓	✓	✓	✓
	Du *et al.* [7]	✓	✓	✓	✓	✓	✓	✓	✓
Cybersecurity	Agrawal *et al.* [2]	✓	✓	✓		✓	✓	✓	✓
	Alazab *et al.* [3]			✓			✓	✓	✓
	Ghimire *et al.* [9]	✓		✓			✓	✓	✓
Blockchain	Nguyen *et al.* [19]	✓	✓	✓	✓	✓	✓	✓	✓
	Qu *et al.* [21]	✓	✓	✓	✓	✓	✓	✓	✓
	Zhu *et al.* 2022 [34]	✓	✓	✓	✓	✓	✓	✓	✓

As summarized in Table 1, most surveys extensively discuss the challenges of efficiency, heterogeneity, privacy in FL systems design, with the surveys from blockchain fileds 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-domincated** cooperation framework is a narrow implementation of the FL systems. Therefore, this survey aim to fill the gap by investigating and surveying the associated tenchnologies 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. In the following section, we will differentiate this survey from other related concepts in the field of FL.

1.2 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 and few-shot FL but goes beyond them. In this section, we will distinguish our survey by highlingting the similarities and differences between these related concepts.

Dcentralized FL.

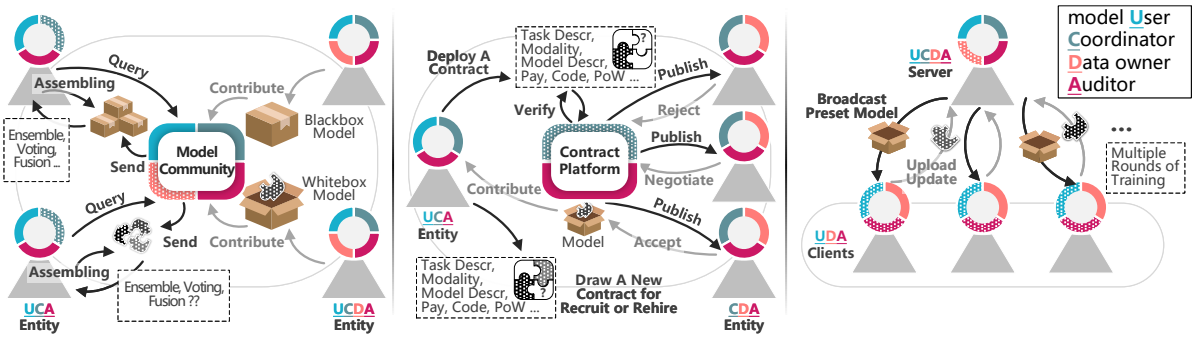
Blockchain-based FL.

Few-shot FL.

1.3 FAIR in FL

FAIR Data Principles: Findable, Accessible, Interoperable, Reusable.

Three cooperation frameworks: query-based FL, contract-based FL, writ-based FL



(a) Query-based FML (b) Contract-based FML (c) Traditional FML

Fig. 1. Cooperation frameworks of FML.

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