

Model-Centric Federated Machine Learning

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Traditional Federated Machine Learning follows a server-dominated training 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 [3].

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 two primary categories: FL system design and FL applications. The initial architectures and concepts for FL systems were summarized by Yang *et al.* [9]. 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 [6, 8]. Following this, an increasing number of surveys have emerged focusing on enhancing FL system design. From the algorithmic perspective, personalized FL [2, 7] aims to learn personalized models for each client to address the challenge of statistical heterogeneity. Besides, the privacy-preserving model aggregation protocols of FL systems also been widely studied and summarized by [1, 4, 5, 10]. Furthermore, Many advance FL architectures had been proposed and summarized, such as Decent Some surveys

1.2 Distinction of Our Survey

However,

Federated learning is promising

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

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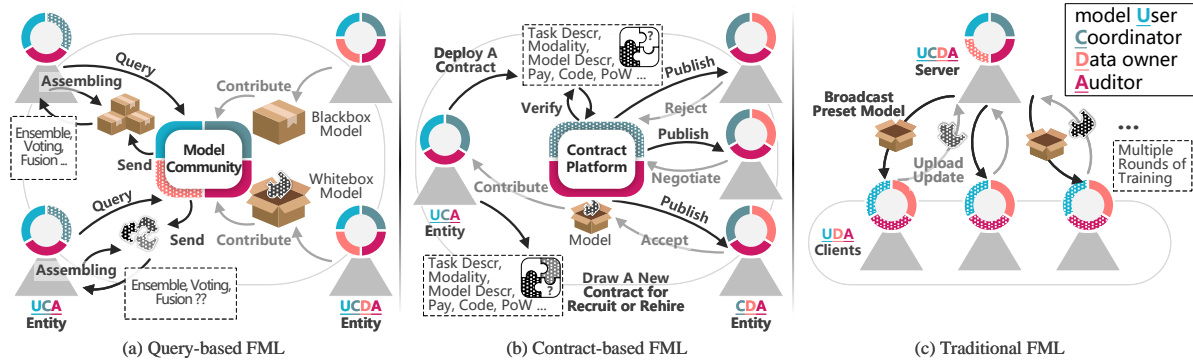


Fig. 1. Cooperation frameworks of FML.

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