Data Quality Control in Federated Instruction-tuning of Large Language Models

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Abstract

By leveraging massive distributed data, federated learning (FL) enables collaborative instruction tuning of large language models (LLMs) in a privacy-preserving way. While FL can effectively extend the data quantity, data quality, despite its significance, is under-explored in current literature of FL of LLMs. In response, we propose a new framework of federated instruction tuning of LLMs with data quality control (FedDQC), which measures data quality to facilitate the subsequent processes of filtering and hierarchical training. Specifically, we firstly propose an efficient data quality evaluation metric, which measures per-sample instruction-response alignment (IRA) at each client side with a single-shot inference. Based on this, samples with relatively low IRA is potentially noisy data, therefore are filtered to mitigate their negative impacts. To further utilize this IRA value, we propose a quality-aware hierarchical training paradigm, where the LLM is progressively fine-tuned from high-IRA to low-IRA data, mirroring the easy-to-hard learning process of humans. We conduct extensive experiments on 4 domain-specific datasets and a general dataset, and compare our method with baselines that are adapted from centralized learning. Results show that our method consistently and significantly improves the performance of LLMs that are trained on mix-quality data via FL.

1 Introduction

For large language models (LLMs) training [1, 2, 3, 4], both the quantity and quality of the training data significantly impact their performance [5, 6]. The scaling law suggests that more training data can lead to more powerful LLMs [7]. However, in specific domains such as healthcare [8] and finance [9], privacy concerns [10] prevent the aggregation of large-scale datasets, making it challenging to expand the dataset scale. Federated Learning (FL) [11], an emerging distributed training approach, preserves privacy by allowing multiple clients to train a unified model collaboratively without sharing their data. This enables dataset scaling while ensuring data privacy [12, 13].

While FL addresses the data quantity issue by incorporating more local clients, it may introduce more data quality issues [14]. In FL, training data for each client are collected from various sources locally, making it difficult to detect low-quality data or errors in local datasets. Such vulnerabilities may adversely affect general model training. Although numerous methods [15, 16, 17, 18, 19] are proposed for data quality control in LLM training, their designs typically require access to the entire training data, making them impractical for FL scenarios. Therefore, in this work, we aim to bridge this gap and address the under-explored issue of federated data quality control in instruction-tuning LLM tasks.

Existing data quality control methods for instruction tuning focused on designing data quality evaluation metrics [20]. These metrics aim to quantify the quality of instruction-response pairs. However, these metrics are not suitable for federated settings for two main reasons. First, adapting these metrics to FL might compromise privacy and computational efficiency. For instance, [21, 16] using external models for evaluation can breach privacy as it involves sending private data out for assessment. Moreover, methods [22, 23] using the influence function [24] require extensive computation, which is impractical in FL where resources are often limited. Second, these metrics are disconnected from the training process. They focus on identifying the most informative yet challenging data points, which often include noisy data mistakenly identified as high-quality [25, 26, 17]. This can destabilize the training process.

To address these two issues in controlling data quality in federated instruction-tuning, we propose a new framework Federated Data Quality Control (FedDQC). The key idea is to directly measure instruction-response relativeness as an aspect of quality evaluation and integrate this measurement with easy-to-hard hierarchical training. Our framework has two main innovative designs: 1) an alignment-based data quality evaluation metric that is computation-efficient without violating privacy. Firstly, motivated by mutual information [27] we proposed the Instruction-Response Alignment (IRA), defining the data quality from the aspect of the relativeness between the instruction and response. In this aspect, the high-scored samples are instruction-response, highly related, and easy to learn. Before the start of training, each client uses the initial global model to evaluate per-sample data quality and select the high-scored samples with the global threshold. This guarantees a globally unified data quality evaluation and data selection standard. 2) A quality-aware hierarchical training that follows an easy-to-hard paradigm. It forces the model to prioritize learning from these highly related samples and then move on to less related, complex data. By starting training with highly aligned data, it helps the model capture the intrinsic features of the data when dealing with varying quality, preventing overfitting to specific errors or noise. This method makes learning more efficient and ensures a more robust model. In addition, by setting the participants in each round to have similar data difficulty, this hierarchical training enables clients to have similar data patterns, thus accelerating convergence.

Our experiments demonstrate that FedDQC not only outperforms all baseline models in both IID (independent and identically distributed) and non-IID settings on four domain-specific datasets but also shows effectiveness on the general dataset, Alpaca-GPT4 [28]. As for computation, we show that the scoring metric IAR consumes only 1% training time for data quality evaluation, making it computation-efficient and scalable for larger datasets.

The contributions of this work are three folds:

- We are the first attempt to tackle the practical issue of federated data quality control in LLM instruciton-tuning.
- We propose an FL data quality control framework FedDQC, which integrates alignment-based quality assessment with quality-aware hierarchical training to enhance efficient and robust instruction-tuning in federated scenarios without violating privacy and computation constraints.
- We experiment on four datasets from specific domains and a general domain dataset, showing the effectiveness of FL data quality control in both IID and NIID scenarios.

2 Related work

2.1 Federated Learning

Federated Learning [29] has emerged as a powerful method for privacy-preserving collaborative training, allowing multiple clients to jointly train a global model without sharing raw data, coordinated by a central server. Existing research on data quality in FL primarily focused on the classification tasks, with noisy label issues. [30] We classify related data quality control works from three levels: client, model and sample level. At the client level, efforts have concentrated on identifying malicious clients [31, 32] through feature [33] or model weight clustering [34]. While at the sample level, studies have typically focused on label correction strategies [35] or confidence-based sample reweighting [36]. At the model level, approaches like distillation [37] or modifying the loss function [38] aimed to increase robustness against noisy labels. However, these methods do not effectively address the unique challenges of federated LLM training, the generation task. This highlights the gap in current approaches and underscores the need for specialized solutions tailored to generative tasks in FL.

2.2 Data quality control

Data quality control is complex and a throughout problem in machine learning [39]. To solve the task for this work, we split the related work into two lines: the traditional data attribution with its adaptation to LLM setting, and current data selection work for LLM.

Data attribution Traditional data attribution methods, used to explain model predictions by identifying influential training examples, are generally categorized into retraining-based and gradient-based techniques. [40] Retraining-based approaches, such as leave-one-out [41], Shapley value [42], and Datamodels [43], estimate the effect of data points by repeatedly retraining the model on different subsets of data. These data attribution approaches are post-hoc and computation costly, making them unsuitable for LLM setting. Gradient-based approaches, like represented point selection [44], TracIn [45], and influence functions [24], estimate training data's impact through parameter sensitivity. Recent studies have developed more efficient adaptations of this gradient-based method for generative tasks [46] and LLM settings, streamlining data selection processes such as pre-training [47] and instruction-tuning in transfer learning scenarios [23]. Despite these advancements in reducing computational complexity through approximations, computing these methods for LLM data selection is still costly due to the increasing size of large model and data volumes.

Data selection for LLMs Current data selection works for LLM instruction-tuning are heuristic and aimed at core set selection. They either depend on a powerful external model for scoring or require iterative training or selection. External model-based scoring techniques, such as AlpaGasus [21], DEITA [16] and INSTAG [48] prompt ChatGPT [1] for various dimension of data quality scoring. While effective, these methods are costly and compromise privacy by requiring direct data sharing. This is particularly problematic in privacy-sensitive settings. Other methods that comply with privacy constraints still require large computation and are not well-suited for local dataset management essential in FL environments. For instance, IFD [25] and MoDS [26] require a computationally intensive initial training stage that may involve low-quality data. Similarly, InstructionMining [17] despite utilizing innovative statistical regression to fit quality influence factors with performance, is dataset-specific and requires retraining. Additionally, approaches like SelectIT [49] and NUGGETS [50] utilize in-context learning but highly depend on the predefined task set, which is sometimes applicable for FL. These challenges underscore the need for a new, locally implementable, efficient scoring method that preserves privacy and reduces computational overhead.

3 Problem formulation

3.1 Background of Federated Learning

In federated instruction tuning, each client holds an instruction-tuning dataset, where each sample is a pair of an instruction $(question, answer)$. Suppose there are total N clients, where the n-th client hold private dataset $\mathcal{D}_n = \{(q^i, a^i) | i = 1, 2, \ldots, |\mathcal{D}_n|\}$ and a local model θ_n^r, where q^i and a^i denote the i-th instruction and answer, r denote the round indices of training. Mathematically, the global objective of federated learning is $\min_\theta L(\theta) = \sum_{n=1}^{N} w_n L_n(\theta)$, where $w_n = \frac{|\mathcal{D}_n|}{\sum_{i=1}^{N} |\mathcal{D}_i|}$ and $L_n(\theta)$ are the dataset relative size and local objective of client n, respectively. The instruction-tuning training loss for the i-th sample is formulated as $L((a^i, q^i), \theta) = -\sum_{j=1}^{l_i} \log p(a_j^i | q_i \oplus a_{<j}^i; \theta)$, where $\oplus$ is the concatenation operator, l_i is the token length of output a^i and $a_{<j}^i$ denotes the tokens before index j. In the basic FL, FedAvg each training round r proceeds as follows: 1) Sever broadcasts the global model θ^r to clients; 2) Each client n performs local model training using t SGD steps to obtain a trained model denoted by $\theta^{r,t}$; 3) Clients upload the locally trained models $\theta^{r,t}$ to the server and the server updates the global model based on the aggregated local model: $\theta^{r+1} = \sum_{n=1}^{N} w_n \theta_n^{r,t}$.

3.2 Data quality control in FL

The data quality control problem is equivalent to reweighting training samples to achieve the best performance on the test set. In the federated setting, we could formulate the federated data quality control problem as follows:

$$\min_{\pi(\cdot)} \mathbb{E}_{(q_T^i, a_T^i) \in \mathcal{D}_T} L((q_T^i, a_T^i), \theta^*) \quad \text{s.t. } \theta^* = \min_\theta \sum_{n=1}^{N} w_n \mathbb{E}_{(q^i, a^i) \in \mathcal{D}_n} \pi((q^i, a^i)) L((q^i, a^i), \theta)$$

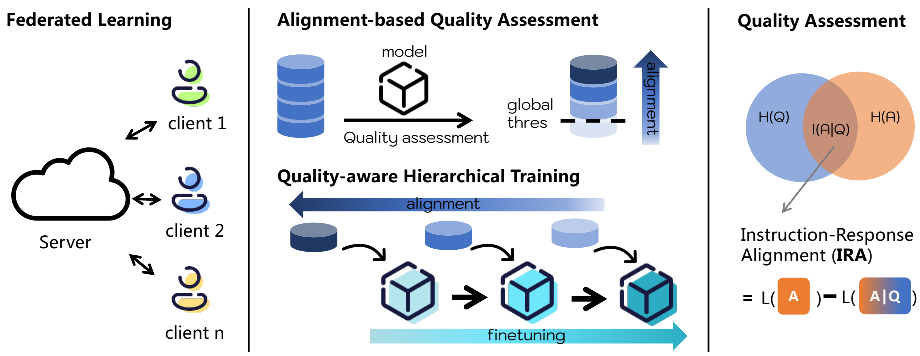


Figure 1: Overview of FedDQC, which consists of two components at the client side. (1) Alignment-based quality assessment: measuring the data quality from the instruction-response alignment perspective. This calculation is analogous to estimating mutual information between instruction and response, illustrated in the right figure; (2) Quality-ware hierarchical training: progressively fine-tuned from high-IRA to low-IRA data, mirroring the easy-to-hard learning process.

where $\pi(\cdot) : \mathcal{D} \rightarrow \mathcal{W}$ is the data quality control function with $\mathcal{W}$ represents the weight set, $\mathcal{D}_T$ and (q_T^i, a_T^i) are the test set and test sample i. The data control quality function could be written as a composition of two functions, $\pi((q^i, a^i)) = g(f((q^i, a^i)))$, where $f : \mathcal{D} \rightarrow \mathcal{S}$ is the scoring function where $\mathcal{D}$ denotes the dataset, $\mathcal{S}$ denotes the score set, and the reweighting function $g : \mathcal{D} \times \mathcal{S} \rightarrow \mathcal{W}$. The scoring function maps each data point with a scalar indicating the data quality and the reweighting function assigns weight to the data sample according to the quality score.

4 Methodology

To address data quality control in FL within computational and privacy constraints, we propose a two-stage FL data quality control framework, FedDQC. Section 4.1 will first give an overview of this framework, Section 4.2 and Section 4.3 will discuss the two components in detail. Lastly, computation, privacy and communication of FedDQC and comparisons with current methods will be discussed in Section 4.4.

4.1 Overview

To control the data quality for training, two steps need to be conducted: data selection based on data quality assessment and high-quality data training. Since in FL, data is preserved at the client side, only the client could assess their data quality and select its data based on the data quality score. In our FedDQC framework, data manipulations are mainly on the client side including the data quality measurement and local data training. The key idea of this framework is to integrate data quality assessment with the training process, which consists of two components the alignment-based data quality assessment and the quality-aware hierarchical training. These components are detailed in Algorithm 1 and illustrated in Figure 1.

The entire pipeline is described as follows. Initially, the server distributes the initial global model θ^0 to each client. Before training, clients assess their data quality using the global model and the data quality evaluation metric f to achieve consistent global data quality measurement: $s_i = f((q^i, a^i), \theta^0)$ for $(q^i, a^i) \in \mathcal{D}_n$. After assigning each data with a quality score s_i, clients select their local data based on a global threshold λ. The selected data are later sorted in descending order and split into K separate hierarchies, $\mathcal{H}_{n1}, \ldots, \mathcal{H}_{nk}$. In the training stage, FedDQC adheres to the FedAvg [11] local update and aggregation paradigm but changes the local dataset training sequence. On the client side, rather than random batching from the whole dataset, each client locally trains their models from the hierarchy $\mathcal{H}_{n1}$ with the highest score of data to the hierarchy $\mathcal{H}_{nK}$ with the lowest score. On the server side, during each round's aggregation, every client updates their model, which is trained on the same level of hierarchy. This guarantees synchronized, easy-to-hard training across all clients and a more consistent aggregation.

4.2 Alignment-based Quality Assessment

As an attempt to control data quality in federated learning, FedDQC needs to assess the data quality under the constraints of privacy and limited computation. We propose a novel data quality evaluation metric, the Instruction-Response Alignment (IRA), which leverages the concept of mutual information [27] to assess the alignment between instructional prompts and responses within local dataset. Specifically, IRA utilizes the initial global model to calculate the difference in loss between unconditioned responses and responses conditioned on their corresponding instructions. The following equation redefines the scoring function f to f_{IRA}:

$$f_{IRA}((q^i, a^i) \in \mathcal{D}, \theta) = L(a^i; \theta) - L((a^i, q^i); \theta)$$

where $L(a^i;\theta) = -\sum_{j=1}^{l_i} \log p(a^i_j | a^i_{<j}; \theta)$ calculates the loss of generating response a^i without given the instruction q^i, $L((a^i, q^i); \theta)$ is the loss given instruction q^i, which is defined in Section 3.1. $\mathcal{D}$ is dataset and θ represents model parameter for data quality evaluation.

This metric relates to the instruction, response, and initial training model to integrate data quality value with learning difficulty. High-score samples usually demonstrate a strong instruction-response relativeness from the perspective of the training model, indicating its learning is easier for the model. This quality evaluation does not compromise privacy and is more computation-efficient than the existing data evaluation metric. Later, based on the global threshold λ, clients select local data for training with the threshold above λ.

4.3 Quality-aware Hierarchical Training

After data selection, the pivotal next step is to start training. In this stage, we propose quality-aware hierarchical training, inspired by the philosophy of curriculum learning (CL) [51], where models learn progressively from easier to harder data, similar to human curricula.

As previously discussed, IRA evaluates instruction-response relativeness and indicates the relative difficulty of model training. Utilizing this metric, we could easily split training data into several hierarchies. The LLM begins with learning basic, instruction-response highly relevant problems, then progresses to applying the learned instruction-following ability to more generalized problems and gradually advances to more complex problems. Moreover, compared to the precisely defined learning scheduler [52], in CL, which precisely decides the sequence of data subsets throughout training, our hierarchical training is more coarse-grained. The number of hierarchies is typically set between 2 to 5, simplifying implementation across various clients.

We summarize the advantages of this method in three ways. 1) This method ensures that the model first establishes a strong foundational understanding, enhancing overall learning effectiveness and robustness; 2) It also ensures a consistent quality of data in each training round, which helps prevent the divergence of the aggregated model; 3) By splitting to fewer hierarchies, it remains the diversity of data within each hierarchy, thereby, prevent overfitting to specific data.

4.4 Discussion

Communication, privacy and computation As pointed out in [53], "privacy and communication efficiency are two primary concerns in FL". Our proposed FedDQC framework does not compromise on either of these aspects, as it only introduces an extra scalar threshold alongside the initial global model in the first round as an additional scalar parameter beyond the model parameters used in FedAvg, which is minimal. Regarding computation, FedDQC adds only one step compared to FedAvg: scoring all the training data, which only requires inferencing rather than training. When keeping the batch size the same for training and inference, the scoring time accounts for approximately 1% of the total training time. See Section 5.3.2.

Comparisons with current methods Compared to NUGGETS [50] and AlpaGasus [21], which utilize an external model for quality evaluation, FedDQC evaluates the data on the client side and preserves local data privacy. Unlike DataInf [22] and NUGGETS [50], which require an extra validation set from the server, these methods become inapplicable in scenarios where the server cannot provide this set. Additionally, their computational cost is related to the size of the validation set. Compared to IFD [25], FedDQC does not require extra dataset adaptation training, thus, is computation effective.

Algorithm 1 FedDQC: Federated Data Quality Control

Initialization: Initial global model: θ^0; Training datasets: $\mathcal{D} = \{\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_N\}$; Number of training rounds: R; Number of hierarchies: K; Global quality threshold: λ
// Scoring & Selecting Stage:
Distribute initial global model θ^0 to each client n
for $n = 1$ to N **do**
  $\mathcal{S}_n = \{s_i : s_i = f_{IRA}((q^i, a^i) \in \mathcal{D}_n, \theta^0)\}$ ▷ Assess data quality of $\mathcal{D}_n$
  $\mathcal{D}'_n = \{(q^i, a^i) \in \mathcal{D}_n, s_i \geq \lambda\}$ ▷ Select data points with quality scores above λ
  Sort $\mathcal{D}'_n$ by quality scores s_i in descending order
  Split sorted $\mathcal{D}'_n$ into hierarchies $\mathcal{H}_{n1}, \mathcal{H}_{n2}, \ldots, \mathcal{H}_{nK}$ with equal size $floor(|\mathcal{D}'_n|/K)$
  ▷ Split local dataset to hierarchies
end for
// Training Stage:
for $k = 1$ to K **do**
  for $r = (R/K) * (k-1) + 1$ to $(R/K) * k$ **do**
    for $n = 1$ to N **do**
      Local update θ_n^r with $\mathcal{H}_{nk}$ ▷ Local easy-to-hard hierarchical training
    end for
  end for
  $\theta^{r+1} = \sum_{n=1}^{N} w_n \theta_n^{r,t}$ ▷ Aggregate local models to update global model θ^r
end for
Return: Global model θ^R

5 Experiments

5.1 Experiment Setup

Dataset and evaluation metric We explore a general dataset Alpaca-GPT4 [28] and four task-specific datasets, PubMedQA [54], FiQA [55], AQUA-RAT [56] and Mol-Instructions [57] covering diverse domains (i.e., medical, finance, math, and molecular science). We apply the accuracy as the evaluation metric for PubMedQA and AQUA-RAT datasets, the BertScore [58] for Mol-Instructions dataset, the GPT-4 comparison win-rate for FiQA and the MT-Bench score for Alpaca-GPT4. For more details please refer to Appendix A.1. To demonstrate and imitate the mixed-quality data in the real world, we constructed synthetic low-quality data on four domain-specific datasets with a proportion of 50%. The low-quality data we construct needs to be challenging for data cleansing and have a significant impact on performance. Therefore, we adopted a method of constructing low-quality data by swapping answers, simulating the scenario of incorrect data responses in real situations. Additionally, this construction method also maintains the content invariance of the corpus. Examples are presented in Appendix A.5.

Models and training settings Our experiment is implemented on the OpenFedLLM [13] framework. We use LLama2-7b[3] as the pre-trained model and adapt Low-Rank Adaptation (LoRA) [59] to achieve fine-tuning. All the experiments are conducted on machines with the same hardware configuration using one NVIDIA GeForce RTX 4090. In all experiments, we use 8-bit quantization with batch size equal to 16, max length equal to 1024, and LoRA rank equal to 64 with a constant $\alpha = 128$. For the federated setting, we consider 100 communication rounds, 5 clients with $8k$ training data in total for domain-specific dataset and 20 clients with $20k$ training data in total for Alpaca-GPT4 dataset. We randomly sample 2 clients for each round with 10 local steps using AdamW [60] optimizer of model training. This setting is equivalent to 3 epochs for local training. For the NIID setting, we follow the Dirichlet distribution (with hyperparameter set to 5 for PubmedQA and FiQA, and 3 for AQUA-RAT and Mol-Instructions). We apply a cosine learning rate schedule according to the round index. The initial learning rate in the first round is $1e-4$, and the final learning rate in the last round is $1e-6$. We use the Alpaca template [61] to format the instruction, as shown in Appendix A.2.

Baselines We include four types of data quality evaluation metrics as data quality control baselines: perplexity (PPL) [62], loss, IFD [25], NUGGETS [50], and DataInf [22]. These four metrics are applied at the data-scoring stage. We select the high-score data for later federated training. Perplexity evaluates how accurately a probability model can predict a sample, usually employed in pre-training

Table 1: Performance comparisons across four datasets on both IID and NIID scenarios. FedDQC achieves the best among all datasets in both IID and NIID settings and even surpasses the full clean data training in all datasets. We bold the best performance among all data quality control methods.

Training Order	**Data Quality high/low**	**Quality Evaluation Metric**	**IID**				**NIID**			
			PubMedQA Acc	**FiQA** Win Rate	**AQUA-RAT** Acc	**Mol-Instructions** BertScore	**PubMedQA** Acc	**FiQA** Win Rate	**AQUA-RAT** Acc	**Mol-Instructions** BertScore
random	high	-	0.750	-	0.299	0.812	0.747	-	0.252	0.812
	low	-	0.681	0.266	0.205	0.809	0.664	0.354	0.205	0.809
random	low	PPL	0.703	0.437	0.224	0.809	0.684	0.544	0.217	0.804
	low	DataInf	0.728	0.457	0.224	0.811	0.675	0.464	0.232	0.807
	low	IFD	0.714	0.622	0.244	0.812	0.699	0.664	0.275	0.815
	low	NUGGETS	0.708	0.565	0.240	0.815	0.682	0.566	0.232	0.814
hierarchical	low	IRA	**0.751**	**0.709**	**0.287**	**0.822**	**0.758**	**0.794**	**0.280**	**0.823**

Table 2: Performance comparisons between various data selection baselines on the Alpaca-GPT4 [28] dataset (IID setting). FedDQC performs the best on open-ended-question benchmark MT-Bench [63].

	FedAvg	**Fedavg+**					**FedDQC**
Quality Evalaution Metric	-	Random	PPL	DataInf	IFD	NUGGETS	IRA
MT-Bench	4.78	4.56	4.58	4.76	4.65	4.38	**4.96**

data cleansing. IFD is a loss-based heuristic quality evaluation metric, that requires additional training to the specific dataset before scoring. NUGGETS define in-context prompting ability as data quality, and DataInf is an influence function adaptation to the generation tasks. In our experiments, DataInf and IFD are slightly adapted to federated scenarios, refer to Appendix A.3 for more details.

5.2 Main result

Applicability on domain-specific dataset We conduct experiments on four domain-specific datasets with synthetic low-quality data in both IID and NIID settings. We compare the FedAvg with the original dataset (referred to high-quality dataset), the synthetic mixed-quality dataset (referred to low-quality dataset), applying 4 data selection baselines and the FedDQC. For FiQA datasets, all results are compared with high-quality data with FedAvg in both settings. To fairly compare all quality evaluation metrics, we adjust the global threshold λ to guarantee the number of training data is the same in all baselines. From Table 1, we could see 1) FedDQC effectively minimizes the misaligned data influence, from the results that FedDQC consistently performs best in all datasets and both settings. 2) When comparing IID and NIID settings, data heterogeneity would slightly affect the global model performance. But this performance drop varies from dataset, for example in FiQA and PubMedQA datasets, in the NIID setting, the heterogeneity affects the global performance before data quality control. 3) FedDQC outperforms the full clean data performance in some settings. There are two reasons. The first is that progressive training methods enable the model to learn well. Secondly, even though we call the data clean, it may still consider some relatively low-quality data, negatively affecting the model performance.

Applicability on general dataset We experimented on the Alpaca-GPT4 [28] dataset in IID setting to show the effectiveness of FedDQC on general dataset. Table 2 shows the performance of full data training and performance after applying four data selection baselines and FedDQC. For all data quality control methods, we select 85% of the original data in each client based on the quality evaluation metric. We evaluate the training performance on an open-ended-question benchmark MT-Bench [63]. From Table 2, we see that (1) FedDQC significantly outperforms other data quality control methods, demonstrating its effectiveness in enhancing the general instruction tuning task's performance. (2) NUGGETS performed the worst among the baselines, even underperforming random selection. This issue may stem from the limited validation set from the server, we designed, which likely resulted in data selections that do not perform well across a sufficiently diverse dataset.

5.3 Emperical analysis of FedDQC

5.3.1 The effectiveness of hierarchical training

To demonstrate the hierarchical training mechanism's effectiveness, we compare random training, training from high-score data to low-score data, and training from low-score data to high-score data on four domain-specific datasets in IID setting, referred in the Table 3 as random, forward and reverse respectively. The experiments show that 1) The relationship between the IRA and easy-to-hard

Table 3: Performance comparisons of random batching and two hierarchical training sequences with different quality evaluation metrics on PubMedQA in IID setting. IRA is a training-aware quality evaluation metric compatible with high-to-low hierarchical training. The red box highlights the best result among all baselines, while the blue box highlights the best performance within the baseline.

	PubMedQA			AQUA-RAT			Mol-Instructions			FiQA		
Train order	**random**	**forward**	**reverse**	**random**	**forward**	**reverse**	**random**	**forward**	**reverse**	**random**	**forward**	**reverse**
random		0.681			0.205			0.809			26.60	
PPL	**0.703**	0.663	0.685	**0.240**	0.217	0.220	**0.809**	0.809	0.807	**0.437**	0.338	0.333
NUGGETS	**0.708**	0.682	0.674	**0.240**	0.193	0.201	**0.815**	0.814	0.810	0.457	**0.681**	0.320
IFD	**0.714**	0.697	0.656	**0.244**	0.217	0.193	0.814	**0.820**	0.799	**0.622**	0.612	0.287
DataInf	**0.728**	0.720	0.717	**0.224**	0.181	0.169	**0.811**	0.806	0.810	**0.565**	0.223	0.300
IRA	0.725	0.718	**0.751**	0.252	0.197	**0.287**	0.817	0.803	**0.822**	0.690	0.432	**0.709**

hierarchical training is closely intertwined, with each aspect mutually reinforcing the other. This synergy is evident in experiments where, compared to random training sequences, the application of reverse sequence training hierarchies led to notable improvements in IRA selection methods across all datasets. Notably, IRA quality selection consistently outperformed other baselines, irrespective of the training sequence. 2) The other quality evaluation metrics do not consistently benefit from the hierarchical training in all datasets, indicating its incompatibility with this hierarchical training.

5.3.2 Computational analysis

We evaluated the additional computational costs of four data quality evaluation metrics compared to IRA during the data scoring stage, alongside their training performance on the PubMedQA dataset under an IID setting in Figure 2. The experiment shows that (1) compared to the total training time in FedAvg, 300.6 minutes, IRA only takes 1% training time for data scoring, making it scalable for large datasets. (2) Compared to PPL, which is too simple to be effective. IRA uses an extra 1 minute, around 0.3% training time, for scoring than PPL but has much higher performance. (3) Compared to the second well-performed metric, DataInf, IRA takes extremely less time, around 1/150 of the scoring time than DataInf. In conclusion, IRA is a computationally efficient, scalable data quality measuring metric that could greatly enhance data quality control.

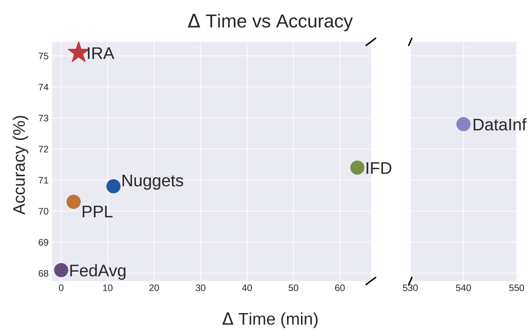


Figure 2: Comparison of additional computation costs and performance gain after applying to different quality evaluation metrics on PubMedQA [54] dataset IID setting. IRA adds minimal computational overhead while significantly enhancing performance through effective data quality control.

5.3.3 Data quality impact analysis

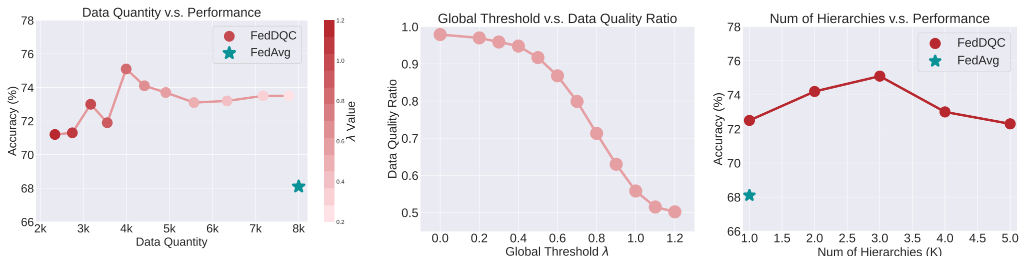
To study how data quality affects training performance, we quantify the dataset's overall quality as the ratio between the number of aligned data and the total data. We conduct experiments with different data quality ratios from 0.5 to full original data on four domain-specific datasets in the IID setting. For FiQA, we use the win rate compared to the original data set trained with FedAvg, therefore, we do not include the point when the quality ratio equals to 1.0 for FedAvg. From Fig 3, we observed (1) FedAvg performance consistently drops as the quality ratio decreases in all datasets. This phenomenon shows that low-quality data significantly affects performance, and the instruction-tuning performance proportionally relates to the data quality ratio. (2) FedDQC consistently outperforms FedAvg under all data quality ratio settings, demonstrating the effectiveness and robustness of FedDQC's data quality control. (3) Even when the data quality ratio is 1.0, meaning the training dataset does not contain synthetic low-quality data, FedDQC outperforms FedAvg across all datasets. This indicates that FedDQC can enhance training even in non-synthetic datasets, indicating its effectiveness.

5.3.4 Hyperparameter ablation

Global threshold To demonstrate the threshold robustness of FedDQCC, we further examine the impact of the global threshold λ on the PubMedQA dataset with the IID setting. Figure 4(a) shows the relationship between total data quantity used for training and performance as the global

(a) PubMedQA (b) FiQA (c) AQUA_RAT (d) Mol-Instructions

Figure 3: Comparison of FedAvg and FedDQC in various data quality ratios. (a)-(d) show the performance under different data quality ratio on PubMedQA [54], FiQA [55], AQUA-RAT [56], and Mol-Instructions [57] datasets respectively. FedDQC is consistently higher than FedAvg in all data quality ratio on four datasets.



(a) Global threshold λ (b) Global threshold v.s. Data quality ratio (c) Number of hierarchies K

Figure 4: Ablation study. (a) Effect of global threshold on overall data quantity and training performance of FedDQC. Experiments show that FedDQC is robust to the global threshold. (b) Effects of global threshold on the quality ratio of all training data. (c) The effect of various hierarchies on training performance in FedDQC training.

threshold λ is adjusted. Different shades of color of the point indicate varying λ values. The graph demonstrates that (1) as the threshold λ changes, the performance of FedDQC remains relatively stable suggesting that FedDQC is insensitive to the threshold λ. (2) Even with varying data quantities, FedDQC consistently outperforms FedAvg, indicating the robustness and effectiveness of the FedDQC approach in maintaining high performance regardless of the threshold used. (3) As Figure 4(b) shows, the data quality ratio in the selected data approaches 1.0 with a smaller threshold. Consequently, as data quantity decreases on the left side, the data quality ratio increases, but the drop in performance is more severe compared to the right side. This asymmetric performance decay around the point with 4k training data indicates that performance is more sensitive to data quantity than data quality.

Number of hierarchies Under the IID setting on PubMedQA, we tune the number of hierarchies in FedDQC $K \in \{1, 2, 3, 4, 5\}$. From Figure 4(c), we see that (1) generally $K = 3$ can lead to better performance. (2) Beyond $K = 3$ further increasing the number of hierarchies leads to a slight decline in accuracy. This suggests that while hierarchical training enhances learning by structuring data from simple to complex, too many hierarchies may reduce diversity, slightly hindering performance.

6 Conclusions and Future works

In this paper, we pioneer the exploration of data quality control in federated instruction-tuning of LLMs. We introduce a novel FL framework, Federated Data Quality Control (FedDQC), which incorporates a new data quality evaluation method, IRA, and integrates this metric with an easy-to-hard hierarchical training. FedDQC comprises two principal components: alignment-based quality assessment and quality-aware hierarchical training. Our extensive experiments demonstrate that FedDQC adds minimal computational overhead while significantly boosting performance through effective data quality control. The integration of IRA and hierarchical training is delicate and exhibits threshold robustness. However, this study did not incorporate a design aimed at enhancing data diversity. We believe that FedDQC can inspire future work focusing on integrating data quality with training processes and include diversity aspects in designation.

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A Appendix

A.1 Dataset and Evaluation Metric

Table 4 shows descriptions of these datasets, including information about the domain, evaluation metrics, number of samples, average length of instruction, and average length of response.

Table 4: Dataset information and evaluation metrics

Dataset	Evaluation metrics	Domain	$\#samples$	$\hat{L}_{inst.}$	$\hat{L}_{Resp.}$
PubMedQA [54]	Acc	medical	211 k	471.1	71.4
FiQA [55]	Win rate	financial	17.1 k	42.1	255.7
AQUA-RAT [56]	Acc	math	97.5 k	77.4	105.7
Mol-Instructions [57]	Bert score	molecular	38 k	110.5	107.8
Alpaca-GPT4 [28]	-	general	52 k	21	163

PubMedQA PubMedQA[1] [54] is a multiple-choice question-answering dataset optimized for medical reasoning. In this paper we utilize the version sourced from PMC-LLama [64]. It features enhanced QA pairs with structured explanations derived from ChatGPT [1], facilitating in-depth medical analysis. PubMedQA dataset consists of 211.3k training samples.

FiQA FiQA dataset[2] is a subset from FinGPT [55], which consists 17.1k financial open question-answers. We split out 200 samples for evaluation and adopted the MT-Bench instruction template (see Table 5) to call ChatGPT [1] API. For the evaluation metric, we utilize the win rate to demonstrate the data quality ratio: $win\_rate = win\_counts/(win\_counts + lose\_counts)$.

Table 5: Alpaca Template for federated instruction tuning

[System]
Please act as an impartial judge and evaluate the quality of the responses provided by two AI assistants to the user question displayed below. You should choose the assistant that follows the user's instructions and answers the user's question better. Your evaluation should consider factors such as the helpfulness, relevance, accuracy, depth, creativity, and level of detail of their responses. Begin your evaluation by comparing the two responses and provide a short explanation. Avoid any position biases and ensure that the order in which the responses were presented does not influence your decision. Do not allow the length of the responses to influence your evaluation. Do not favor certain names of the assistants. Be as objective as possible. Don't provide your explanation, output your final verdict by strictly following this format: "[[A]]" if assistant A is better, "[[B]]" if assistant B is better, and "[[C]]" for a tie.
[User Question]
{question}
[The Start of Assistant A's Answer]
{answer_a}
[The End of Assistant A's Answer]
[The Start of Assistant B's Answer]
{answer_b}
[The End of Assistant B's Answer]

AQUA_RAT The AQUA-RAT [56] dataset[3] is a large-scale mathematical dataset with a collection of around 100k algebraic word problems. Each problem in the dataset is accompanied by a detailed, step-by-step solution narrative, articulated in natural language. This dataset consists of 97.5k training samples and 245 test samples. We use accuracy as the evaluation metric.

[1] https://huggingface.co/datasets/axiong/pmc_llama_instructions
[2] https://huggingface.co/datasets/FinGPT/fingpt-fiqa_qa
[3] https://huggingface.co/datasets/aqua_rat

Mol-Instructions The Mol-Instructions [57] dataset [4] consists of a subset: biomolecular text instructions, specifically designed for natural language processing tasks in bioinformatics and chemoinformatics. It encompasses six distinct information extraction and question-answering (QA) tasks, structured through 53k detailed instructions. This design supports advanced NLP applications that require precise and context-specific understanding in the scientific domains of biology and chemistry. Our experiment only samples the open-qa task with 37k training set and 1k test set. For evaluation, the BertSocre [58], an automatic evaluation metric for text generation, is applied on a predefined test set of size 200.

Alpaca-GPT4 The Alpaca-GPT4 dataset [61] utilizes a self-instruct method to extract instructional data from ChatGPT [1], making it a widely used resource for instruction tuning. For our evaluations, we distinguish between two benchmark categories: close-ended and open-ended. The close-ended benchmarks [65] we employed include MMLU [66] for knowledge, BBH [67] and DROP [68] for reasoning, HumanEval [69] for coding, and CRASS [70] for counterfactual scenarios. For open-ended evaluation, we use Vicuna-Bench [71] and MT-Bench [63], with the latter being particularly notable for its common application in assessing instruction-following capabilities through two-turn conversation tasks.

A.2 Prompt Template

Table 6: Alpaca Template for federated instruction tuning

```
Below is an instruction that describes a task. Write a response that appropriately completes the request.

### Instruction:
{Instruction}

### Response:
```

A.3 Baselines

Perplexity: Perplexity, a probability-based metric, is defined as the exponentiated average of the negative log-likelihoods of a tokenized sequence $X = (x_0, x_1, \ldots, x_t)$. Specifically, the perplexity of X, denoted as $\mathrm{PPL}(X)$, is calculated using the formula $\mathrm{PPL}(X) = \exp\left\{-\sum_i^t \log p_\theta(x_i \mid x_{<i})/t\right\}$, where $\log p_\theta(x_i \mid x_{<i})$ represents the log-likelihood of the ith token, conditional on its preceding tokens $x_{<i}$. This measure is frequently employed to data cleaning within a pre-trained corpus [72].

DataInf Influence functions, a gradient-based scoring method, rely on the model's performance on a validation set. DataInf, as introduced by [22], stands out as the first computationally efficient approximation of influence functions that can be practically implemented in LLMs. This Hessian-based standard influence functions, provide scores $\mathrm{DataInf}(x_j)_i = \nabla L(x_j;\theta^\star) H_{\theta^\star}^{-1} \nabla L(x_i;\theta^\star)$ for every x_i in $\mathcal{D}_k$ and x_j in $\mathcal{D}_{val}$, where $\theta^\star$ denotes the parameters of the model trained on the training dataset, and $H_{\theta^\star}$ is the Hessian matrix of the empirical loss function. However, this method needs the model's convergence, which is unreal. To adapt to a federated setting, we first use the full dataset trained for 100 rounds for domain-specific datasets and 200 rounds for the general dataset. Then using this well-trained model to estimate the data influence score.

IFD The Instruction-Following Difficulty (IFD) metric is calculated by the formula $\mathrm{IFD}_\theta(Q, A) = \frac{s_\theta(A|Q)}{s_\theta(A)}$, where $s_\theta(A) = -\frac{1}{N}\sum_{i=1}^N logP(w_i^A|w_1^A, ..., w_{i-1}^A;\theta), s_\theta(A|Q) =$

[4] https://huggingface.co/datasets/zjunlp/Mol-Instructions

Table 7: Comparison between the performance of high-quality data and low-quality data according to the IRA metric.

	PubMedQA Acc	AQUA-RAT Acc	Mol-Instructions Acc	FiQA Win rate
Full data	0.750	0.2992	0.812	-
High-score	0.73	0.2559	0.822	0.7810
Low-score	0.723	0.1732	0.800	0.3733

$-\frac{1}{N}\sum_{i=1}^{N} logP(w_i^A|Q, w_1^A, ..., w_{i-1}^A; \theta)$. IFD metric measures the difficulty of following instructions of a given sample. We train our model for 20 rounds on the targeted dataset, and subsequently, this pre-trained model is used for experiments with IFD as the scoring metric.

NUGGETS NUGGETS leverages the disparity between one-shot and zero-shot scores to calculate a definitive gold score for each instruction. Exploiting the inherent contextual learning capabilities of large models.

A.4 How Data quality affects training performance

We compare the high-score proportion of data with the low-score proportion of data and show that the data quality indeed affects training performance. See Table 7.

A.5 Case Study

A.5.1 Examples of synthetic low-quality data

Table 8, 9, 10, 11 shows examples of synthetic low-quality data in 4 domain-specific datasets. Each dataset showcases a pair of data, including the questions, the authentic correct answers, and the incorrect answers generated by swapping the correct ones. The synthetic low-quality data is created by pairing the same question with its incorrect answer.

A.5.2 Examples of scored data

Figures 5, 6, 7, 8 shows examples of scored data in 4 mixed-quality domain-specific datasets. Each dataset's size is 8k, with 50% low-quality data generated by swapping correct answers. The remaining 50% is considered high-quality data. We use IRA as the scoring metric and show typical data examples with scores in top 1% and lowest 1%.

Typically, high-quality data scores high and low-quality data scores low. This is because the incorrect answers in low-quality data significantly diminish the instruction-response relativeness, leading to an increase in IRA. However, the high-quality data example in Figure 5 scores low, due to the presence of complicated and verbose input. Consequently, the model finds it challenging to establish the relativeness between the instruction and response.

Table 8: Synthetic low-quality data in PubMedQA

Question	**Correct Answer**	**Incorrect Answer**
Given your profession as a doctor, please provide responses to the medical questions using the patient's description. Analyze the question given its context. Give both long answer and yes/no decision. ###Question: Does mineralocorticoid receptor blockade inhibit accelerated atherosclerosis induced by a low sodium diet in apolipoprotein E-deficient mice? ###Context: A low-sodium diet (LSD) was shown to increase both angiotensin II (AngII) and aldosterone levels ...	In E0 mice, Epl inhibited LSD-accelerated atherosclerosis, despite the elevation of renin and aldosterone levels. It is therefore suggested that the atherogenic action of LSD could be mediated, at least in part, by activation of the mineralocorticoid receptor. In addition, eplerenone may have direct anti-inflammatory actions. ###Answer: yes	Therefore, the technique could be considered an alternative method in increasing the keratinized tissue for cases that have a minimal amount of keratinized tissue. ###Answer: yes
In your capacity as a doctor, it is expected that you answer the medical questions relying on the patient's description. Analyze the question given its context. Give both long answer and yes/no decision. ###Question: Do simultaneous placement of an interpositional free gingival graft with nonsubmerged implant placement? ###Context: Various surgical techniques target achieving adequate keratinized tissue around dental implants ...	Therefore, the technique could be considered an alternative method in increasing the keratinized tissue for cases that have a minimal amount of keratinized tissue. ###Answer: yes	In E0 mice, Epl inhibited LSD-accelerated atherosclerosis, despite the elevation of renin and aldosterone levels. It is therefore suggested that the atherogenic action of LSD could be mediated, at least in part, by activation of the mineralocorticoid receptor. In addition, eplerenone may have direct anti-inflammatory actions. ###Answer: yes

Table 9: Synthetic low-quality data in FiQA

Question	Correct Answer	Incorrect Answer
Share your insights or perspective on the financial matter presented in the input. ###Question: What one bit of financial advice do you wish you could've given yourself five years ago?",	Compound interest. Next time you buy a 100$ toy realize that if you save it - in x years that 100$ you saved and invested could potentially be more than 100$ where as most likely whatever you're buying will be worth much less.	If the building has no income, it also probably has minimal expenses. The heat, water and electricity costs are nearly zero. They are letting the value depreciate, and taking it off the taxes. I also suspect the condition of the building is poor, so any effort to make the building productive would be very costly. Many cities combat this by setting the tax on empty buildings or empty lots at a much higher rate. ...
Utilize your financial knowledge, give your answer or opinion to the input question or subject . Answer format is not limited. ###Question: Tax deductions on empty property	If the building has no income, it also probably has minimal expenses. The heat, water and electricity costs are nearly zero. They are letting the value depreciate, and taking it off the taxes. I also suspect the condition of the building is poor, so any effort to make the building productive would be very costly. Many cities combat this by setting the tax on empty buildings or empty lots at a much higher rate. ...	Compound interest. Next time you buy a 100$ toy realize that if you save it - in x years that 100$ you saved and invested could potentially be more than 100$ where as most likely whatever you're buying will be worth much less.

Table 10: Synthetic low-quality data in AQUA-RAT

Question	Correct Answer	Incorrect Answer
###Instruction: Choose the correct option for the following math question. ###Question: 1000 men have provisions for 15 days. If 200 more men join them, for how many days will the provisions last now? ###Options: A. 12.8 B. 12.4 C. 12.5 D. 16.8 E. 92.7	###Rationale: 1000*15 = 1200*x x = 12.5 ###Answer: OPTION C IS CORRECT.	###Rationale: Explanation: Let the sum of money be x then (x × 4 × 8)/100 = (560 × 12 × 8)/100 x × 4 × 8 = 560 × 12 × 8 x × 4 = 560 × 12 x = 560 × 3 = 1680 ###Answer: OPTION D IS CORRECT.
###Instruction: Choose the correct option for the following math question. ###Question: If simple interest on a certain sum of money for 8 years at 4% per annum is same as the simple interest on Rs. 560 for 8 years at the rate of 12% per annum then the sum of money is ###Options: A. Rs.1820 B. Rs.1040 C. Rs.1120 D. Rs.1680 E. None of these	###Rationale: Explanation: Let the sum of money be x then (x × 4 × 8)/100 = (560 × 12 × 8)/100 x × 4 × 8 = 560 × 12 × 8 x × 4 = 560 × 12 x = 560 × 3 = 1680 ###Answer: OPTION D IS CORRECT.	###Rationale: 1000*15 = 1200*x x = 12.5 ###Answer: OPTION C IS CORRECT.

Table 11: Synthetic low-quality data in Mol-Instructions

Question	Correct Answer	Incorrect Answer
Answer this question truthfully ###Question: What is the predicted relative molecular mass of the protein encoded by PVAS2?	The predicted relative molecular mass of the protein encoded by PVAS2 is 65810 Da.	Resonance Raman spectroscopy is a form of spectroscopy used to analyze the vibrational, rotational, and other structural characteristics of molecules.
Answer this question truthfully ###Question: What is Resonance Raman spectroscopy?	Resonance Raman spectroscopy is a form of spectroscopy used to analyze the vibrational, rotational, and other structural characteristics of molecules.	The predicted relative molecular mass of the protein encoded by PVAS2 is 65810 Da.

Scored data examples in PubMedQA

High-quality, High-score
IRA score: 4.08

[Instruction]
Considering your role as a medical practitioner, please use the patient's description to answer the medical questions.
Analyze the question given its context. Give both long answer and yes/no decision.
[Input]
###Question: Does [Hemorrhagic shock increase the occurrence of bacterial translocation]?
###Context: To determine whether hemorrhagic shock (HS) increases the occurrence of bacterial translocation (BT). 100 patients were divided into 4 groups: control group (group I, 34 patients); group with hemorrhagic shock (HS) caused by closed blunt abdominal trauma (group II, 23); group caused by closed blunt abdominal trauma without HS (group III 15); and group with HS caused by intra-abdominal viscus hemorrhage (group IV 28). Preoperative and postoperative samples were taken from peripheral blood, visceral peritoneal swab, portal vein blood, ileal mesenteric lymph node, liver and spleen biopsy respectively for aerobic and anaerobic culture. The positive culture rates of these groups were 6%, 65%, 13%, 68% respectively. The difference between the control and experimental groups was significant($P < 0.05$). The difference was also significant between group I and II and between I and IV ($P < 0.01$), whereas it was not significant between I and III, and between II and IV ($P > 0.05$).
[Output]
HS increases the occurrence of BT.

###Answer: yes

High-quality, Low-score
IRA score: -0.61

[Instruction]
Given your background as a doctor, please provide your insight in addressing the medical questions based on the patient's account.
Analyze the question given its context. Give both long answer and yes/no decision.
[Input]
###Question: Does globulin-platelet model predict minimal fibrosis and cirrhosis in chronic hepatitis B virus infected patients?
###Context: To establish a simple model consisting of the routine laboratory variables to predict both minimal fibrosis and cirrhosis in chronic hepatitis B virus (HBV)-infected patients. We retrospectively investigated 114 chronic HBV-infected patients who underwent liver biopsy in two different hospitals. Thirteen parameters were analyzed by step-wise regression analysis and correlation analysis. A new fibrosis index [globulin/platelet (GP) model] was developed, including globulin (GLOB) and platelet count (PLT). GP model = GLOB (g/mL) × 100/PLT (× 10(9)/L). We evaluated the receiver operating characteristics analysis used to predict minimal fibrosis and compared six other available models. Thirteen clinical biochemical and hematological variables [sex, age, PLT, alanine aminotransferase, aspartate aminotransferase (AST), albumin, GLOB, total bilirubin (T.bil), direct bilirubin (D.bil), glutamyltransferase, alkaline phosphatase, HBV DNA and prothrombin time (PT)] were analyzed according to three stages of liver fibrosis (F0-F1, F2-F3 and F4). Bivariate Spearman's rank correlation analysis showed that six variables, including age, PLT, T.bil, D.bil, GLOB and PT, were correlated with the three fibrosis stages (FS). Correlation coefficients were ...
[Output]
By establishing a simple model using available laboratory variables, chronic HBV-infected patients with minimal fibrosis and cirrhosis can be diagnosed accurately, and the clinical application of this model may reduce the need for liver biopsy in HBV-infected patients.

###Answer: yes

Figure 5: The examples of scored data in mixed-quality PubMedQA dataset include a high-quality datapoint with a high score and a high-quality datapoint with a low score.

Scored data examples in FiQA

High-quality, High-score
IRA score: 3.16

[Instruction]
Share your insights or perspective on the financial matter presented in the input.
[Input]
###Question: On a debt collection agency's letter, what does "balance" refer to?
[Output]
The balance is the amount due.

Low-quality, Low-score
IRA score: -0.28

[Instruction]
Utilize your financial knowledge, give your answer or opinion to the input question or subject . Answer format is not limited.
[Input]
###Question: How can a person with really bad credit history rent decent housing?
[Output]
I can't give you a detailed answer because I'm away from the computer where I use kMyMoney, but IIRC to add investments you have to create new transactions on the 'brokerage account' linked to your investment account.

Figure 6: The examples of scored data in mixed-quality FiQA dataset include a high-quality datapoint with a high score and a low-quality datapoint with a low score.

Scored data examples in AQUA-RAT

High-quality, High-score
IRA score: 1.92

[Instruction]
###Instruction: Choose the correct option for the following math question.
[Input]
###Question: What should come in place of question mark(?) in the following equation?
8597 – ? = 7429 – 4358
###Options:
A. 5706
B. 5526
C. 5426
D. 5626
E. None of these

[Output]
###Rationale: 8597 – ? = 7429 – 4358
? = 5526

###Answer: OPTION B IS CORRECT.

Low-quality, Low-score
IRA score: -0.04

[Instruction]
###Instruction: Choose the correct option for the following math question.
[Input]
###Question: A jar contains only red, yellow, and orange marbles. If there are 3 red, 5 yellow, and 4 orange marbles, and 2 marbles are chosen from the jar at random without replacing any of them, what is the probability that 2 yellow, 1 red, and no orange marbles will be chosen?
###Options:
A. 1/60
B. 1/45
C. 2/45
D. 3/22
E. 6/22

[Output]
###Rationale: P= 16 = 16+3 = 19 = S
O = 15 =15+3 =18 = R
SIMILARLY,
P = 16 = 16+3 = 19 = S
R = 18 = 18+3 = 21 = U
I = 9 = 9+3 = 12 = L
Y = 25 = 25 +3 = 28 = B
A = 1 = 1+3 = 4 = D
SO ANS IS
SULB

###Answer: OPTION D IS CORRECT.

Figure 7: The examples of scored data in mixed-quality AQUA-RAT dataset include a high-quality datapoint with a high score and a low-quality datapoint with a low score.

Scored data examples in Mol-Instructions	
High-quality, High-score IRA score: 3.95 [Instruction] Answer this question truthfully [Input] ###Question: How long after the beginning of the secondary aggregation process does the mitotic coefficient reach a first maximum? [Output] The mitotic coefficient reaches a first maximum 8 hours after the beginning of the secondary aggregation process.	Low-quality, Low-score IRA score: -0.63 [Instruction] Answer this question truthfully [Input] ###Question: What are system invariants? [Output] The results suggest that multiple pathways exist in soybean to regulate expression of Aox genes.

Figure 8: The examples of scored data in mixed-quality Mol-Instructions dataset include a high-quality datapoint with a high score and a low-quality datapoint with a low score.

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